Betting Against Other Betas*

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Abstract

Using several multifactor models, I find strong "betting against beta" effects - flat relations between betas and expected returns - for most non-market factors in US and international stock markets. "Arbitrage portfolios" designed to profit from these effects earn average returns similar to those of the factors, with substantially reduced risk. Betas are persistent, indicating that the factor models successfully capture important dimensions of covariation in returns. Previously-proposed explanations for the betting against market beta effect do not explain these results. These findings raise questions about the economic content of existing empirical factor models and the covariance-based expected return paradigm.

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JEL Classifications: G11, G12, G15

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1 Introduction

Two main theoretical predictions of arbitrage pricing theory (APT hereafter, Ross (1976)) are that the slope of the security market plane - the surface describing the relation between betas and expected returns - with respect to the beta on any factor is equal to that factor's risk premium, and that betas are the only determinants of the cross section of expected security returns. Empirically, several studies contextualized within the capital asset pricing model (CAPM hereafter) demonstrate that the security market line is flatter than predicted by theory, a phenomenon dubbed the "betting against beta" effect by Frazzini and Pedersen (2014, FP hereafter). While there is little empirical support for a relation between market beta and expected stock returns, a large body of research has shown that the cross section of expected stock returns is related to variables other than beta. These findings have led to several papers proposing alternative APT-style multifactor models that augment the market factor with additional factors designed to explain the plethora of pricing effects. Despite the prominence of the APT-style models in the empirical literature, there is little evidence on whether betas with respect to these additional factors are, as predicted by APT, determinants of the cross section of expected stock returns.[1]

In this paper, I examine the cross-sectional relation between betas on other (i.e. non-market) factors and expected stock returns. Using several well-established and contemporary multifactor models, I find strong evidence of betting against beta effects for most factors. Specifically, the security market plane slopes with respect to betas on nearly all factors in the US and international stock markets are significantly lower than the average excess returns generated by the corresponding factors (the factor risk premia).[2] In most cases, the security market plane slopes are insignificant. I also find that, despite the flatness of the security market plane, the factors capture important dimensions of covariation among stock returns, since stock-level betas on most factors are highly persistent. The combination of large factor risk premia, flat security market plane, and highly-persistent betas presents a strong challenge to APT, the premise of which is that any divergence between betas and

[1]Notable exceptions are Daniel and Titman (1997) and Brennan, Chordia, and Subrahmanyam (1998), who conclude that the cross section of expected stocks returns is related to characteristics in ways not captured by betas, and Davis, Fama, and French (2000), who conclude the opposite.

[2]Throughout this paper, I use "factor" to refer to both the underlying economic factor and the factor portfolios used in empirical factor models, and distinguish only when required for clarity.

expected security returns presents an arbitrage opportunity.

I then develop and test a methodology for constructing "arbitrage portfolios" designed to profit from the apparent arbitrage opportunity. The arbitrage portfolios take a long position in the factor and a short position in a "hedge portfolio" designed to be highly correlated with the the factor but earn an expected return equal to the associated security market plane slope. As intended, the arbitrage portfolios have very similar average excess returns to, but substantially less risk than, the corresponding factors. The results indicate that the factor risk premia can be earned while taking significantly less risk than inherent in the factors themselves.

Finally, I investigate whether the betting against beta effects have a common driver. I find that the excess returns of the arbitrage portfolios are not highly correlated. Furthermore, explanations for the betting against market beta phenomenon put forth by previous research cannot explain the betting against beta effects for other factors. These findings suggest that there is no common driver of the betting against beta effects across factors.

In sum, the evidence strongly suggests that while extant factor models are highly successful at capturing dimensions of common variation in stock returns, betas with respect to these factors are not determinants of the cross section of expected stock returns. The results question the effectiveness of covariance-based models of expected security returns as a description of observed market pricing.

The analytical framework for my tests is a modification of the APT equilibrium pricing relation. According to APT, the expected excess return of any security i, $E[r_i]$, is given by $E[r_i] = \boldsymbol{\beta_i'}\boldsymbol{\lambda}$ where $\boldsymbol{\beta_i} = (\beta_{i,1}, \beta_{i,2}, \ldots, \beta_{i,k})'$ is a k-vector of security i's betas on the set of k priced factors and $\boldsymbol{\lambda} = (\lambda_1, \lambda_2, \ldots, \lambda_k)'$ is a k-vector of factor risk premia, which are the same as the security market plane slopes. I modify this relation by allowing the security market plane slopes deviate from $\boldsymbol{\lambda}$ by amounts $\boldsymbol{\psi} = (\psi_1, \psi_2, \ldots, \psi_k)'$. Specifically, the model I test is $E[r_i] = \boldsymbol{\beta_i'}(\boldsymbol{\lambda} - \boldsymbol{\psi})$. If $\psi_j = 0$ for all j, then APT holds and no arbitrage opportunities exist. $\psi_j \neq 0$ for some j indicates that the security market plane slope with respect to beta on factor j is different than λ_j. Most relevant to my findings, $\psi_j > 0$ indicates that the security market plane slope with respect to beta on factor j is less than the factor risk premium λ_j, a condition I refer to as a betting against beta effect for factor j.

I estimate the security market plane in the US, Asian, and European stock markets using eight factor models previously proposed in the empirical asset pricing literature, seven of which are multifactor models. Specifically, I examine a one-factor market model (CAPM hereafter), and the multifactor models proposed by Fama and French (1993, FF model hereafter), Carhart (1997, FFC model hereafter), Fama and French (2015, FF5 model hereafter), Hou, Xue, and Zhang (2015, Q model hereafter), Stambaugh and Yuan (2016, SY model hereafter), Daniel, Hirshleifer, and Sun (2019a, DHS model hereafter), and Daniel, Mota, Rottke, and Santos (2019b, DMRS model hereafter).[3]

To estimate the security market plane slopes $(\lambda_j - \psi_j)$, I construct test asset portfolios by sorting stocks into value-weighted portfolios based on pre-formation estimates of betas with respect to different factors. I then run a cross-sectional regression of average portfolio excess returns on the post-formation betas of these test assets. For most factors j, the estimate of $\lambda_j - \psi_j$, which is the security market plane slope with respect to beta on factor j, is close to zero and statistically insignificant. This suggests that the security market plane is flat along most dimensions. Importantly, the portfolios used in these tests have strong variation in post-formation betas, and the post-formation betas are highly-correlated with pre-formation betas, indicating that the factor models do indeed capture dimensions of commonality (risk) in stock returns and that stock-level exposures to these risks are persistent. To measure the magnitude of the betting against beta effects (ψ_j), I take λ_j to be the average excess return of the factor j, and subtract from λ_j the estimated slope coefficient $\lambda_j - \psi_j$. The estimates of ψ_j are all positive and most are large and highly significant, indicating that there are strong betting against beta effects with respect to most factors.

While the empirical tests conducted on each factor model are the same, differing economics underlying each factor model lead to somewhat different interpretations of the results for different models. The CAPM, FF, FFC, FF5, Q, and DMRS models are intended to capture sources of priced risk in the economy.[4] The results provide no evidence, however, that the factors in these models actually capture priced sources of risk. This finding is particularly surprising for the DMRS model, because the factors in this model are modifications of the factors in the FF5 model explicitly intended to isolate only the priced component of the FF5 model factors. The SY and DHS models are motivated as "mispricing" models, and the factors in these models are intended to capture common sources of mispricing. The fact that betas with respect to the factors in these models are highly persistent over long horizons (my focal tests use five years of data to estimate pre-formation betas), suggests that despite the intent of these models, the factors are actually capturing sources of fundamental, albeit

[3] Due to factor data availability, analyses of Asian and European stocks use only the CAPM, FF, FFC, and FF5 models.

[4] Fama and French (2015) are somewhat ambiguous on this point, claiming that the firm-level equilibrium model that motivates the factors in the FF5 model holds regardless of whether stocks are priced rationally (based on risk) or irrationally (mispriced).

unpriced, risk.

In the spirit of APT, I construct the arbitrage portfolios for each of the non-market factors in each model by taking a long position in the factor j portfolio and a short position in a "hedge portfolio".[5] The main idea underlying APT is that if two well-diversified portfolios have the same betas and different expected returns, then an arbitrage portfolio that is long the portfolio with a higher expected return and short the portfolio with a lower expected return will generate a riskless positive excess return. The assumption of efficient markets underlying APT prohibits such riskless profit, thus inseparably linking expected returns to betas. The evidence of a flat security market plane combined with a strong factor structure in stock returns, however, suggests that betas and expected returns are not as closely tied as predicted by APT, and that arbitrage portfolios may exist.

The factor j portfolio has, by definition, unit beta with repect to the given factor and an expected excess return equal to the factor risk premium λ_j. The hedge portfolio is designed to also have a beta of one with respect to the given factor, but an expected excess return that is driven by the corresponding security market plane $\lambda_j - \psi_j$. The expected excess return of the arbitrage portfolio, then, is the factor risk premium (λ_j) minus the given slope of the security market plane $(\lambda_j - \psi_j)$, which is exactly equal to the magnitude of the betting against beta effect ψ_j. I implement the hedge portfolio by combining decile portfolios formed by sorting on pre-formation betas in a manner intended to minimize the hedging error, which is equivalent to minimizing the variance of the arbitrage portfolio. My implementation produces hedge portfolios whose returns are highly correlated with the returns of the factor portfolio but have average excess returns that, reflecting the flatness of the security market plane, are close to zero. As a result, the arbitrage portfolios generate average excess returns that are similar to those of the factor portfolios, with substantially less risk than the factor portfolios. My ability to generate arbitrage portfolios that perform as designed strongly suggests that the theoretical equilibrium predicted by APT is not an accurate description of actual security market prices.

Finally, I investigate whether there is a common economic force underlying all of the betting against beta effects. If the same force drives all of these effects, then I would expect the returns of the arbitrage portfolios to be highly correlated. This is not the case. The correlations between the excess returns of most pairs of arbitrage portfolios are close to

[5] Working within the CAPM framework, FP create arbitrage portfolios for the market factor by taking long (short) positions in low (high) beta stocks, and refer to these portfolios as "betting against beta" portfolios. While the objectives for my arbitrage portfolios are the same as those of FP, my portfolio construction methodology differs substantially from that of FP.

zero, and many are negative. I also investigate whether explanations for the betting against market beta effect proposed by previous work can explain my findings. FP claim that the betting against beta effect is driven by leverage- and margin-constrained investors seeking to increase expected returns by overweighting high-beta stocks in their portfolios. Bali, Brown, Murray, and Tang (2017) find evidence that the betting against beta effect is the result of lottery demand: high-beta stocks tend to also have lottery-like characterstics, causing investors who demand stocks with lottery-like features to overweight high-beta stocks in their portfolios, thus increasing their prices and decreasing future returns.[6] Wang, Yan, and Yu (2017) find evidence that the combination of reference-dependent preferences and mental accounting causes investors to exhibit risk-seeking investment behavior in stocks for which they have unrealized losses, thus resulting in high demand, among such stocks, for stocks with high betas. Using tests similar to those presented in these previous papers, I find little evidence that any of these explanations for the betting against market beta effect can explain my results.

My work contributes to three main lines of the empirical asset pricing literature. First, I add to the work documenting the flatness of the security market line. The initial evidence of this effect was presented by Black, Jensen, and Scholes (1972). Several subsequent papers, including Fama and French (1992), Black (1993), and FP, show that this phenomenon persists for decades after its discovery, and FP show that the effect exists in several asset classes and across many geographic regions. I extend this line of work by showing that, in a multifactor setting, the security market plane is flatter than theoretically predicted along most dimensions, which is tantamount to the existence of betting against beta effects with respect to most factors.

Second, I add to the growing line of work that offers a skeptical view of extant empirical factor models. The seminal papers in this area are Daniel and Titman (1997) and Brennan et al. (1998), who find that the size and book-to-market ratio characteristics are related to expected stock returns in ways not captured by betas. More recently, Lewellen, Nagel, and Shanken (2010) question the strength of the relations between empirical factor portfolios such as those examined throughout this paper and true macroeconomic risk factors. Golubov and Konstantinidi (2019) question whether the value premium is compensation for risk at all. Finally, Daniel et al. (2019b) argue that factor portfolios are exposed not only to priced risk, but also to unpriced sources of common variation, and develop a methodology for removing

[6] Asness, Frazzini, Gormsen, and Pedersen (2019) find that both leverage constraints and lottery demand contribute to low-risk anomalies.

unpriced risk from standard factor portfolios. My findings that the security market plane is flat along most dimensions go a step further and suggest that the average excess returns of the factor portfolios are in no way compensation for exposure to priced risks. My evidence that even betas with respect to the factors constructed by Daniel et al. (2019b), which are explicitly designed to capture only priced risk, are unrelated to expected stock returns, is particularly strong evidence in favor of this conclusion.

Third, I add to the line of research that aims to produce APT-style multifactor models that explain cross-sectional variation in average stock returns. The seminal paper in this field is Fama and French (1993), whose three-factor FF model was designed to explain cross-sectional variation in average stock returns associated with size and the book-to-market ratio. Next came Carhart (1997), whose four-factor FFC model augmented the FF model with a factor designed to capture the momentum effect documented by Jegadeesh and Titman (1993). These two models served as the workhorse models in the literature for nearly 20 years. During this time, a large number of papers presented evidence of variation in average stock returns that is not explained by these models.[7] In an effort to summarize and span the predictive power documented by these papers, several new factor models were developed. The most notable of these are the FF5, Q, SY, DHS, and DMRS models that I examine in this paper. The papers proposing these new factor models present evidence that these models outperform the more traditional FF and FFC models at explaining variation in average stock returns. However, in stark contrast to the predictions of APT, my findings indicate that very few, if any, of these factors capture sources of priced risk. My results therefore question the substance and interpretation of commonly-used empirical factor models. While my findings may be less surprising for the SY and DHS models, because these models are intended to capture mispricing and not risk, the fact that I find similar results for the risk-based models suggests that large positive average excess returns of the factors in all of the models are due to mispricing and not compensation for risk. Finally, given that the objective of these factor models is to explain the large number of documented anomalies, my findings are ironic because they suggest that each new factor brings with it a new betting against beta anomaly.

The remainder of this paper proceeds as follows. In Section 2 I present the analytical framework that motivates my tests, rigorously define what is meant by a betting against beta effect, and develop my main hypotheses. Section 3 provides strong evidence of betting against beta effects with respect to nearly all factors in the US stock market. In Section

[7] Fama and French (2015), Hou et al. (2015), McLean and Pontiff (2016), and Linnainmaa and Roberts (2018) list and categorize many of the variables shown to predict the cross section of future stock returns in a manner not captured by the FF and FFC models.

4 I describe the design and implementation of the arbitrage portfolios, and show that they deliver the predicted performance. Section 5 shows that similar results hold in international equity markets. Section 6 examines several potential explanations for my findings. Section 7 concludes.

2 Analytical Framework and Hypotheses

In this section, I describe the analytical framework that motivates my empirical tests and develop my hypotheses in the context of this framework.

2.1 Analytical Framework

The analytical framework I employ throughout this paper is a modification of APT. The assumption underlying APT is that the excess return of any security i in any period t, r_i (I omit period subscripts for clarity), is given by

$$r_i = E[r_i] + \sum_{j \in \{M\}} \beta_i^j f_j + \epsilon_i \tag{1}$$

where $E[r_i]$ is the expected excess return of security i, defined as the expected return of the security minus the risk-free rate, $\{M\}$ is the set of factors that drive all correlation between the returns of different securities, β_i^j is the sensitivity of the return of security i to factor j, f_j is factor j's period t innovation, and ϵ_i is the idiosyncratic component of security i's period t return. The main insight of APT is that, if securities are priced so as to not permit arbitrage (a non-zero expected excess return with no risk), then the equilibrium pricing equation is given by

$$E[r_i] = \sum_{j \in \{M\}} \beta_i^j \lambda_j, \tag{2}$$

where λ_j is the risk premium for factor j. Deviations from this pricing equation present arbitrage opportunities. Stated alternatively, APT stipulates that, in an arbitrage-free equilibrium, the slope of the security market plane with respect to β_j must be equal to λ_j.

In this paper, I continue to assume the same return dynamics as given in equation (1), but consider an alternative equilibrium pricing relation in which the expected excess return of any security i is given by

$$E[r_i] = \Psi + \sum_{j \in \{M\}} \beta_i^j (\lambda_j - \psi_j). \tag{3}$$

This pricing relation differs from the APT equilibrium given in equation (2) in two ways. Most importantly, the security market plane slopes are now given by $\lambda_j - \psi_j$, where the ψ_j represent deviations from the slopes predicted by APT. Second, Ψ is the expected excess return of a risky security that has $\beta_i^j = 0$ for all j. While the focus of this paper is on the security market plane slopes, allowing the security market plane intercept to be non-zero enables the equilibrium pricing equation (3) to be viewed as a multifactor extension of the equilibrium relations proposed by Black (1972, 1993) and FP.

2.2 Hypotheses

When $\psi_j = 0$ for all $j \in \{M\}$, and $\Psi = 0$, then equation (3) is equivalent to the equilibrium pricing relation under APT. The focal null hypotheses that I examine in this paper are $\psi_j = 0$ for each $j \in \{M\}$. If all of these null hypotheses hold, the security market plane slopes are as predicted by APT. The alternative hypotheses are therefore $\psi_j \neq 0$ for each $j \in \{M\}$. A non-zero value of ψ_j indicates a deviation in the slope of the security market plane along the β^j dimension from the APT equilibrium. FP test similar hypotheses using a one-factor market model and provide strong evidence that $\psi_{MKT} > 0$, where MKT is the market factor, a phenomenon they refer to as "betting against beta". In this paper, I borrow FP's terminology and refer to $\psi_j > 0$ as a "betting against beta" effect for factor j. The value of ψ_j measures the size of the betting against β^j effect.

3 Tests of Betting Against Beta Effects in the US Stock Market

I first test my hypotheses using data from the US stock market. The tests are conuducted in the context of eight previously-established factors models. The first is the traditional CAPM, which includes only a market factor ($MktRF$). While previous work has already shown that a strong betting against market beta effect exists when using the CAPM model, I include this model to demonstrate that I find similar results in my sample. Second, I use the three-factor FF model, which includes a market factor ($MktRF$), a size factor (SMB), and a value factor

(HML). Third, I examine the four-factor FFC model that augments the FF model with a momentum factor (MOM) designed to capture variation in returns associated with the momentum effect of Jegadeesh and Titman (1993). The fourth factor model I use is the five-factor FF5 model, which includes a market factor ($MktRF$), a slighlty different size factor ($SMB5$) from that used in the FF and FFC models, a value factor (HML), an investment factor (CMA), and a profitability factor (RMW). The fifth model is the four-factor Q model that includes a market factor ($MKTQ$), a size factor (ME), an investment factor (IA), and a profitability factor (ROE). Sixth, I use the four-factor SY model that includes the market factor ($MktRF$), a size factor ($SMBSY$), and two mispricing factors, one of which derives from variables related to firm performance ($PERF$) and the other of which derives from variables related to decisions made by firms' management ($MGMT$). The seventh factor model I examine is the three-factor DHS model that augments the market factor ($MktRF$) with short-horizon ($PEAD$) and long-horizon (FIN) mispricing factors. Finally, I use the five-factor DMRS model that includes a market factor ($MktRF^*$), a size factor (SMB^*), a value factor (HML^*), an investment factor (CMA^*) and a profitibility factor (RMW^*), each of which is designed to capture the priced component of the corresponding factor from the FF5 model.

3.1 Data

The data used for the analyses of the US stock market are gathered from several sources. Stock return, price, and shares outstanding data are from the Center for Research in Security Prices. Excess returns for the $MktRF$, SMB, HML, MOM, $SMB5$, RMW, and CMA factors, as well as the risk-free asset returns, are from Ken French's data library.[8] Excess returns for the $MKTQ$, ME, IA, and ROE factors are from Chen Xue's website.[9] $SMBSY$, $MGMT$, and $PERF$ factor excess returns are from Robert Stambaugh's website.[10] $PEAD$ and FIN factor excess returns are from Lin Sun's website.[11] Finally, excess returns for the $MktRF^*$, SMB^*, HML^*, CMA^*, and RMW^* factors are from Kent Daniel's website.[12]

[8] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[9] http://global-q.org/factors.html
[10] http://finance.wharton.upenn.edu/~stambaug/
[11] https://sites.google.com/view/linsunhome
[12] http://www.kentdaniel.net/research.php

3.2 Factor Risk Premia

The empirical tests in this paper assume that the excess return of any factor portfolio in any period t is equal to the factor's risk premium plus the factor innovation. Specifically, the period t excess return of factor j, $r_{j,t}$, is assumed to be given by

$$r_{j,t} = \lambda_j + f_{j,t} \tag{4}$$

where $f_{j,t}$ is the period t innovation in factor j and $E[f_{j,t}] = 0$ for all t. I therefore take the average excess return of factor j as an estimate of the factor's risk premium λ_j.

Table 1 presents the average and standard deviation of the monthly excess returns for each factor in each model for the period to be covered by my tests. Throughout this paper, all excess returns are reported in percent per month. The tests pertaining to any given factor model examine the period beginning in either July 1963 or five years after the data for the factors in the given model are available, whichever is later. As will be described in more detail in Section 3.3, starting the tests a minimum of five years after the factor data are available enables me to create test assets by sorting on betas estimated using five years of data prior to the period examined in the test. Tests using the CAPM, FF, and FFC models cover return months beginning in July of 1963. Tests using the FF5, Q, SY, and DHS models begin in July 1968, January 1972, January 1968, and July 1977, respectively. All tests end in December 2018, except for those using the SY model, which end in December of 2016 because data for the SY model factors are only available through 2016. The table shows that the mean monthly excess factor returns are all positive, ranging from 0.13% per month for the SMB^* factor in the DMRS model to 0.67% per month for the FIN factor in the DHS model. With the exception of the SMB factor in the FF and FFC models (t-statistic = 1.68), the $SMB5$ factor in the FF5 model (t-statistic = 1.21), the ME factor in the Q model (t-statistic = 1.95), and the SMB^* factor in the DMRS model (t-statistic = 1.63), all of which are size factors, the average excess factor returns are all significant at the 5% level.

3.3 Test Assets

The tests assets used to estimate the security market plane slopes are portfolios formed by sorting on pre-formation estimates of stocks' betas. The objective of the test asset construction methodology is to generate test assets that have large dispersion in post-formation factor exposures. At the end of each month t, I calculate the pre-formation beta for each stock i relative to each factor j in each factor model M using a time-series regression of the form

$$r_{i,t} = \alpha_i + \sum_{j \in \{M\}} \beta_i^j r_{j,t} + \epsilon_{i,t} \tag{5}$$

where $r_{i,t}$ is the excess return of stock i in month t, $r_{j,t}$ is the month t excess return of factor j, and $\{M\}$ is the set of factors in factor model M. The pre-formation betas are taken to be the slope coefficients from the regression. The regressions use monthly data from months $t-59$ through t, inclusive. If a stock has fewer than 24 monthly return observations during the estimation period, I do not include the stock in the test asset portfolios. Summary statistics for the betas, presented in Table IA1 and Section IA1 of the Internet Appendix, indicate that for the tests of the CAPM, FF, and FFC model, which cover portfolio formation months t (one-month-ahead return months $t+1$) from June (July) 1963 through November (December) 2018, the average month has 3880 stocks. The number of stocks in the average month covered by the analyses using each of the other factor models is greater than 4000.[13]

I next sort all US-based common stocks listed on the NYSE, AMEX, and NASDAQ into decile portfolios based on an ascending ordering of each of the measures of betas. The month $t+1$ excess return for each decile portfolio is then taken to be the market capitalization-weighted (value-weighted hereafter) average month $t+1$ excess return of all stocks in the portfolio. Market capitalization is calculated as the number of shares outstanding times the price of the stock as of the end of month t. Since the portfolios I examine are value-weighted, stocks with missing market capitalization values are not included in the portfolios.

Table 2 presents the average monthly excess return, post-formation betas, and alpha for each of the beta-sorted portfolios. The post-formation betas and alpha for each portfolio are calculated by running the regression given in equation (5) with the portfolio excess return as the dependent variable using returns for all months during the period covered by the tests of the given model. In addition to presenting results for each of the decile portfolios, the table presents results for a zero-cost portfolio that is long the decile 10 portfolio and short the decile 1 portfolio ($10-1$ portfolio). While the $10-1$ portfolios are not included in the set of test assets that I will use to estimate the security market plane slopes, they are useful here for several reasons. First, a positive and significant $10-1$ portfolio average excess return suggests that stocks with high values of the given beta have higher expected returns than stocks with low values of given beta. Second, the post-formation betas of the $10-1$ portfolio are equal to the difference between corresponding betas of the tenth and first decile portfolios,

[13] Since my choice to focus on pre-formation betas calculated from five years of monthly data is arbitrary, in Section IA2 and Tables IA2-IA5 of the Internet Appendix, I demonstrate that my findings are similar when I use pre-formation betas estimated from 12 months of daily return data.

and thus give an indication of whether the test asset construction methodology successfully generates test assets with significant post-formation dispersion in factor exposure. Third, the alpha of the $10-1$ portfolio is an estimate of $-\sum_{j\in\{M\}}(\beta^j_{Post,10}-\beta^j_{Post,1})\psi_j$, where $\beta^j_{Post,p}$ is the post-formation beta of the pth decile portfolio with respect to factor j. The regression therefore provides some preliminary evidence regarding the main hypotheses. If the $10-1$ portfolio's alpha is significant, it suggests that at least one of the ψ_j is not zero.

The table shows that the average excess returns of the $10-1$ portfolios range from -0.25% to 0.31% per month and are all statistically insignificant. Of the 29 $10-1$ portfolios, 18 have positive average excess returns and 11 have negative average excess returns. Examination of the individual decile portfolios reveals no consistent pattern in average returns across the deciles of any of the beta measures. The results provide no evidence of cross-sectional relations between betas and expected stock returns.

The post-formation betas demonstrate that the portfolio construction procedure successfully generates portfolios with strong dispersion in factor exposures. In all but one case (the exception is β^{PEAD} in the DHS model), the $10-1$ portfolio's post-formation beta corresponding to the beta upon which the portfolios were formed (e.g. the post-formation exposure to the SMB factor, β^{SMB}_{Post}, for the $10-1$ portfolio formed by sorting on β^{SMB}), is positive, economically large, and highly significant. The post-formation betas corresponding to the sort variable tend to increase across the decile portfolios. The large dispersion in the post-formation betas corresponding to the sort variable indicate that stock returns have a strong factor structure that is reflected in the factor models and that individual stock factor loadings are highly persistent.

Notably, several of the $10-1$ portfolios have large and significant post-formation betas that do not correspond to the sort variable. One such example is the $10-1$ portfolio formed by sorting on β^{ME} using the Q factor model. As intended, this portfolio's post-formation exposure to the ME factor of 1.38 (t-statistic = 16.01) is large and highly statistically significant. However, this portfolio also has large post-formation exposure of -0.73 (t-statistic = -6.76) to the IA factor. It is for this reason that it is difficult to draw any conclusions about the slopes of the security market plane or betting against beta effects from the results in Table 2. In this example, it is possible that the reason the $10-1$ portfolio generates an insignificant average excess return is that the positive exposure to the ME factor and negative exposure to the IA factor may have offsetting effects on the portfolio's expected return.

Finally, the results show that 25 of the 29 $10-1$ portfolios have negative alpha, 14 of which are statistically significant. Examination of the individual decile portfolios' alphas also suggests that, for most of the beta measures, the alphas tend to be lower for stocks with higher betas. While these results strongly suggest that betting against beta effects exist with respect to many factors, as discussed in the previous paragraph, the fact that several of the $10-1$ portfolios have large loadings on more than one factor makes it impossible to precisely attribute these effects to specific factors from these results.

3.4 Security Market Plane and Betting Against Beta

To measure the security market plane slopes, I run cross-sectional regressions of average portfolio excess returns on the portfolios' post-formation betas. The regressions are of the form

$$\overline{r_p} = \Psi + \sum_{j \in \{M\}} (\lambda_j - \psi_j)\beta^j_{Post,p} + \epsilon_p \tag{6}$$

where $\overline{r_p}$ and $\beta^j_{Post,p}$ are the average excess portfolio return and post-formation beta, respectively, of portfolio p (reported in Table 2), ϵ_p is the residual term, and Ψ and $\lambda_j - \psi_j$ for $j \in \{M\}$ are the coefficients estimated by the regression. I run one regression for each factor model. For the CAPM model, the regression has 10 observations corresponding to the 10 portfolios formed by sorting on β^{MktRF}, and for the FF5 model (for example), the regression has 50 observations corresponding to 10 decile portfolios for each of the five betas in the FF5 model. The slope coefficient $\lambda_j - \psi_j$ from these regressions provides an estimate of the slope of the security market plane along the β^j dimension. I also calculate an estimate of the betting against beta effect, ψ_j, by subtracting the estimated slope coefficient $\lambda_j - \psi_j$ from the estimate of λ_j (reported in Table 1). A positive value of ψ_j indicates that the slope of the security market plane along the β^j dimension is less than the factor risk premium, meaning that a betting against β^j phenomenon exists.

The point estimates and associated t-statistics for $\lambda_j - \psi_j$, shown in Table 3, provide little evidence of cross-sectional relations between betas and expected stock returns. While 23 of the 29 estimated values of $\lambda_j - \psi_j$ are positive, only five are statistically significant at the 5% level. Additionally, a few of these five significant results are potentially "double-counted" in the sense that they result from the same or a related factor in different models. Specifically, the estimated values of $\lambda_{HML} - \psi_{HML}$ are 0.20% (t-statistic = 3.19) and 0.13 (t-statistic = 2.16) in the FF and FFC models, respectively, indicating a positive cross-sectional relation between β^{HML} and expected stock returns. However, in the FF5 model, the $\lambda_{HML} - \psi_{HML}$ estimate of 0.03 (t-statistic = 0.51) is small and statistically insignificant, but the estimate of $\lambda_{RMW} - \psi_{RMW}$ of 0.19 (t-statistic = 3.48) is large and highly significant. This finding is consistent with evidence in Novy-Marx (2013) of strong interactions between the value and profitability effects and with Fama and French (2015), who acknowledge the redundancy of the HML factor in their five-factor model. The results suggest that the positive relation between β^{HML} and expected returns detected using the FF and FFC models results from a positive correlation between β^{HML} and β^{RMW}, and that all three of these statistically significant coefficients are a manifestation of the positive relation between β^{RMW} and expected stock returns.[14]

While the results in Table 3 provide limited evidence that the security market plane has a positive slope with respect to any of the betas, the estimates of ψ_j provide strong evidence that betting against beta effects hold not only with respect to the market factor, but with respect to most other, if not all other, factors in the factor models I examine. All of the ψ_j estimates are positive, ranging from 0.09% per month for ψ_{RMW} in the FF5 model to 0.76% per month for ψ_{PERF} in the SY model, and 24 of the 29 are statistically significant at the 5% level. Additionally, for two of the five insignificant estimates of ψ_j, estimates from the same factor in different models generate significant results. Specifically, using the FF model, the estimated value of ψ_{HML} is an insignificant 0.12% per month (t-statistic = 1.88), but using the FFC and FF5 models the ψ_{HML} estimates of 0.19% (t-statistic = 3.12) and 0.30% (t-statistic = 4.79) per month are highly significant. Similarly, using the DHS model, the estimate of ψ_{MktRF} of 0.44% per month (t-statistic = 1.89) is insignificant, but the estimates of ψ_{MktRF} in other models are all highly significant, ranging from 0.39% (t-statistic = 2.26) using the FFC model to 0.71% (t-statistic = 3.97) using the SY model.[15]

In sum, the results in Table 3 suggest that the security market plane is flat along most dimensions and provide strong evidence of betting against beta effects with respect to most factors.

[14] In untabulated results, I find that the correlation between β^{HML}_{Post} and β^{RMW}_{Post} is 0.26.

[15] In Section IA3 and Table IA6 of the Internet Appendix, I repeat the tests using an alternative methodology motivated by Fama and MacBeth (1973). This alternative methodology produces (necessarily) the same point estimates for $\lambda_j - \psi_j$ and ψ_j, but different, and generally higher, standard errors. The results using this alternative methodology are consistent with those presented in Table 3. Specifically, using the alternative methodology I find that none of the security market plane slopes are significant and most of the betting against beta effects are significant.

4 Arbitrage Portfolios in the US Stock Market

The strong betting against beta effects documented in the previous section suggest that the equilibrium pricing relation predicted by the APT does not hold and that it may be possible for investors to profit from the flatness of the security market plane. However, the results presented thus far are based on post-formation measures of beta calculated from the entire time-series of monthly portfolio returns. Investors attempting to construct portfolios to capture the betting against beta effects would not know the post-formation betas at the time of portfolio construction. It is therefore unclear from these results whether investable portfolios that profit from the betting against beta effects can be constructed. In this section, I develop and test a methodology for constructing "arbitrage portfolios" that profit from the betting against beta effects using only information available at the time of portfolio construction.

4.1 Design of Arbitrage Portfolios

The motivation for the construction of the arbitrage portfolios comes from APT. I assume that the excess return of any security i in any period t is given by equation (1). For a well-diversified portfolio p, the idiosyncratic component of the excess return disappears and the random component of the return is purely a function of factor innovations (I omit period t subscripts for simplicity):

$$r_p = E[r_p] + \sum_{j \in \{M\}} \beta_p^j f_j. \tag{7}$$

If two well-diversified portfolios $p1$ and $p2$ have the same betas on all factors, i.e. $\beta^j := \beta_{p1}^j = \beta_{p2}^j$, then the difference in the period t excess returns of these portfolios, or equivalently the excess return of a portfolio that is long portfolio $p1$ and short portfolio $p2$, is

$$\begin{aligned} r_{p1} - r_{p2} &= E[r_{p1}] + \sum_{j=\{M\}} \beta^j f_j - E[r_{p2}] - \sum_{j=\{M\}} \beta^j f_j \\ &= E[r_{p1}] - E[r_{p2}], \end{aligned} \tag{8}$$

which is a constant, meaning that the long-short portfolio has no risk. If portfolios $p1$ and $p2$ have different expected excess returns, then this constant is not zero, and assuming without loss of generality that $E[r_{p1}] > E[r_{p2}]$, a portfolio that is long portfolio $p1$ and short portfolio $p2$ earns a positive and risk-free excess return. I refer to any portfolio satisfying these criteria as an arbitrage portfolio.

The main premise of APT is that arbitrage portfolios should not exist in efficient markets because they generate a risk-free return in excess of the risk-free rate. The results demonstrating the existence of widespread betting against beta effects, however, suggest that it may be possible to create arbitrage portfolios, or at least portfolios with properties that approximate those of theoretical aribitrage portfolios. Specifically, consider a portfolio Arb_k that is long the factor k and short some other portfolio, which I refer to as the $Hedge_k$ portfolio. The expected returns of the securities held in the $Hedge_k$ portfolio are assumed to follow the equilibrium pricing relation, given in equation (3), which reflects the betting against beta effects. Letting r_k^{Arb}, r_k^{Hedge}, and r_k^{Factor} be the excess returns of the the Arb_k portfolio, the $Hedge_k$ portfolio, and the factor k, respectively, and assuming that the $Hedge_k$ portfolio is sufficiently diversified to eliminate idiosyncratic risk, the excess return of the the Arb_k portfolio is

$$\begin{aligned} r_k^{Arb} &= r_k^{Factor} - r_k^{Hedge} && (9) \\ &= \lambda_k + f_k - E[r_k^{Hedge}] - \sum_{j \in \{M\}} \beta^j_{Hedge,k} f_j && (10) \end{aligned}$$

where $\beta^j_{Hedge,k}$ is the $Hedge_k$ portfolio's beta on factor j. Assuming that factor innovations are independent, i.e. $Cov(f_j, f_l) = 0$ for $l \neq j$, the variance of the Arb_k portfolio is

$$\begin{aligned} Var(r_k^{Arb}) &= Var(f_k - \sum_{j \in \{M\}}^{n} \beta^j_{Hedge,k} f_j) \\ &= (1 - \beta^k_{Hedge,k})^2 Var(f_k) + \sum_{j \in \{M\}, j \neq k} (\beta^j_{Hedge,k})^2 Var(f_j). && (11) \end{aligned}$$

The theoretical arbitrage portfolio has zero variance, which is satisfied if and only if $\beta^k_{Hedge,k} = 1$ and $\beta^j_{Hedge,k} = 0$ for $j \neq k$. If these conditions are satisfied, the expected excess return of the Arb_k portfolio is

$$E[r_k^{Arb}] = \psi_k - \Psi \sum_{i=1}^{N} w_i^{Hedge,k}, \tag{12}$$

where $w_i^{Hedge,k}$ is the weight of security i in the $Hedge^k$ portfolio and N is the number of securities in this portfolio. Equation (12) says that $E[r_k^{Arb}]$ is a function of the size of the betting against beta effect for factor k, given by ψ_k, and the sum of the weights in the hedge portfolio, $\sum_{i=1}^{N} w_i^{Hedge,k}$. If the $Hedge_k$ portfolio requires zero net investment, meaning that $\sum_{i=1}^{N} w_i^{Hedge,k} = 0$, then the expected excess return of the arbitrage portfolio is purely determined by the size of the betting against β^k effect:

$$E[r_k^{Arb}] = \psi_k. \tag{13}$$

If the slope of the security market plane with respect to β^k is zero, as the results in Table 3 suggest is the case for most factors k, then $\psi_k = \lambda_k$ and $E[r_k^{Arb}] = \lambda_k$, meaning that the arbitrage portfolio has the same expected return as the factor.

In practice, constructing a $Hedge_k$ portfolio that perfectly satisfies the conditions $\beta_{Hedge,k}^k = 1$, $\beta_{Hedge,k}^j = 0$ for $j \neq k$, and $\sum_{i=1}^{N} w_i^{Hedge,k} = 0$, is challenging. However, insofar as it is possible to construct a $Hedge_k$ portfolio that approximately satisfies these conditions, the performance of the resulting Arb_k portfolio should approximate that of the theoretical arbitrage portfolio. The practical objectives, therefore, are to construct a tradable $Hedge_k$ portfolio that minimizes the variance of the resulting Arb_k portfolio's returns while also ensuring that $\sum_{i=1}^{N} w_i^{Hedge,k} \approx 0$.

The $Hedge_k$ portfolio weights that minimize the variance of the Arb_k portfolio can be estimated from a regression of excess factor returns on the excess returns of the candidate securities using data from a period prior to the time at which the portfolios are constructed. If the weights estimated from historical return data produce a $Hedge_k$ portfolio with future returns that are highly correlated with the factor returns, the risk of the resulting Arb_k portfolio will be low.

The objective that the net investment of the $Hedge_k$ portfolio be small can be achieved by imposing the restriction $-W \leq \sum_{i=1}^{N} w_i^{Hedge,k} \leq W$ on the regression, for some value W. Setting $W = 0$ constrains the net investment of the $Hedge_k$ portfolio to be exactly zero. Any such restriction, however, is likely to result in a decreased correlation between the $Hedge_k$ portfolio and factor excess returns, and thus an increase in the risk of the Arb_k portfolio. Furthermore, there is good reason to suspect that, for all factors other than the market factor, the weights resulting from the unconstrained regression will approximately satisfy the zero-net investment objective, thus alleviating the need to explicitly impose the constraint. The reason is as follows. As can be seen from equation (11) above, the variance of the Arb_k portfolio is increasing in $\beta_{Hedge,k}^j$ for $j \neq k$. Thus, the $Hedge_k$ portfolio weights that minimize the variance of the Arb_k portfolio would be expected to produce a hedge portfolio that has $\beta_{Hedge,k}^j \approx 0$ for $j \neq k$, meaning that a well-constructed $Hedge_k$ portfolio should satisfy $\beta_{Hedge,k}^{MKT} \approx 0$, where MKT is the market factor. Barring the situation where there is a strong tendency for the long positions in the $Hedge_k$ portfolio to have high market betas and the short positions to have low market betas, or vice versa, the condition $\beta^{MKT}_{Hedge,k} \approx 0$ suggests that $\sum_{i=1}^{N} w_i^{Hedge,k} \approx 0$. Stated alternatively, the logic is that a portfolio that is net long (short) stocks is likely to have a positive (negative) market beta. Thus, a portfolio of stocks with no exposure to market risk is likely to require approximately zero net investment. Ultimately, whether the unconstrained regression produces hedge portfolio weights that approximately satisfy the zero-net investment criterion is an empirical question that I address when I examine the performance of the arbitrage portfolios.

4.2 Implementation of Arbitrage Portfolios

I propose an implementation of the $Hedge_k$ portfolio, for factors other than the market factor, that uses decile portfolios formed by sorting stocks on lagged values of β^k as the set of securities available for inclusion in the $Hedge_k$ portfolio.[16] Specifically, at the end of each month t, I sort all stocks into decile portfolios based on an ascending ordering of β^k measured as of the end of month $t-6$. Thus, the values of β^k used to sort the stocks into portfolios at the end of month t are estimated from regressions using monthly data covering months $t-65$ through $t-6$, inclusive. I then calculate daily value-weighted excess returns of each of the decile portfolios for each day in months $t-5$ through t, using the market capitalizations as of the end of month t as weights.[17] Finally, I calculate the weights of each decile portfolio in the $Hedge_k$ portfolio, $w_i^{Hedge,k}$ for $i \in \{1, 2, \ldots, 10\}$, by running the time-series regression

$$r^{Factor}_{k,d} = \gamma + \sum_{i=1}^{10} w_i^{Hedge,k} r_{i,d} + \epsilon_{k,d} \tag{14}$$

using the six months of daily excess returns covering months $t-5$ through t, where $r^{Factor}_{k,d}$ and $r_{i,d}$ are the day d factor excess return and decile portfolio i excess return, respectively, and $\epsilon_{k,d}$ is the day d error term. The month $t+1$ excess return of the $Hedge_k$ portfolio is then taken to be

$$r^{Hedge}_{k,t+1} = \sum_{i=1}^{10} w_i^{Hedge,k} r_{i,t+1} \tag{15}$$

[16] FP develop a methodology for generating an arbitrage portfolio, which they refer to as a betting against beta portfolio, that captures the betting against market beta effect. While the design of FP's portfolio is substantially different than mine, both methodologies have the same objectives of capturing the profits offered by a betting against beta effect while minimizing risk.

[17] To ensure the accuracy of the daily portfolio returns, I require that all stocks in the hedge portfolio have a non-missing return for each day trading day during months $t-5$ through t, inclusive.

where the $w_i^{Hedge,k}$ are from regression (14) and $r_{i,t+1}$ is the month $t+1$ excess return of value-weighted decile portfolio i. Finally, the month $t+1$ excess return of the Arb_k portfolio is

$$r_{k,t+1}^{Arb} = r_{k,t+1}^{Factor} - r_{k,t+1}^{Hedge}. \quad (16)$$

I use six-month lagged values of β^k to sort stocks into decile portfolios to eliminate the impact of estimation error in the values of β^k on the portfolios' weights in the $Hedge_k$ portfolio. Had I not used lagged values on β^k to form the portfolios, then insofar as the data points driving the errors in the estimates of β^k come from months $t-5$ through t, using data from this same time period to run regression (14) will generate biased estimates of the optimal $Hedge_k$ portfolio weights $w_i^{Hedge,k}$. The likely result would be low post-formation correlation between the factor and the hedge portfolio. Since the objective of the implementation of the $Hedge_k$ portfolio is to generate a portfolio with a month $t+1$ return that is highly-correlated with that of the factor, ensuring that the estimates of $w_i^{Hedge,k}$ are unbiased is important. The choice to lag by six months represents a tradeoff between the improved accuracy in the hedge that comes from the inclusion of more data in the regression used to calculate the weights and the decreased accuracy that may result from potentially time-varying betas. However, as shown in Section IA4 and Table IA7 of the Internet Appendix, the performance of the arbitrage portfolios is nearly unchanged when using three or 12 months, instead of six months, of daily data to calculate the hedge portfolio weights.

4.3 Arbitrage Portfolio Performance

Table 4 describes the performance of the arbitrage portfolios for the non-market factors in each of the factor models. I do not include market factors in this analysis because the optimal hedge portfolio for the market factor is simply the portfolio with weights proportional to the total market capitalization of the stocks in the given decile portfolio, and the hedge portfolio is then exactly the same as the market factor.

The results demonstrate that the arbitrage portfolios perform as intended. The arbitrage portfolios' average excess returns ($\overline{r^{Arb}}$) are all positive and highly significant, ranging from 0.18% per month (t-statistic = 2.92) for the SMB factor in the FFC model to 0.65% per month (t-statistic = 6.65) for the FIN factor in the DHS model. As intended by the portfolio design, values of $\overline{r^{Arb}}$ are similar to the corresponding sizes of the betting against beta effects (ψ, repeated from Table 3 to facilitate comparison). The correlation between values of $\overline{r^{Arb}}$ and ψ, calculated across all factors in all models, is 0.89. Furthermore, as expected given the flatness of the security market plane along most dimensions, the values of $\overline{r^{Arb}}$ are also similar to the corresponding factor risk premia (λ, repeated from Table 1 to facilitate comparison). The correlation between values of $\overline{r^{Arb}}$ and λ across all factors and models is 0.97.

With the exception of the DMRS model, the arbitrage portfolios also have substantially reduced risk relative to the factors themselves. Specifically, excluding the $PEAD$ factor in the DHS model, the standard deviations of the monthly arbitrage portfolio excess returns are lower than those of the corresponding factor excess returns by between 27% (for the ROE factor in the Q model, $(2.55 - 1.86)/2.55$) and 54% (for the $SMB5$ factor in the FF5 model, $(3.02 - 1.39)/3.02$). The fact that the arbitrage portfolio for the $PEAD$ factor does not have substantially less risk than the corresponding factor is not surprising given that the $10 - 1$ portfolio formed by sorting on β^{PEAD} is the only such portfolio to not generate significant post-formation exposure to the corresponding factor (see Table 2). This result suggests that the $PEAD$ factor does not capture a source of risk that is common to many stocks. My finding that the arbitrage portfolios for factors in the DMRS model do not have substantially less risk than the corresponding factors is quite surprising because these factors are explicitly designed to capture sources of priced risk that are common to many stocks. If this were indeed the case, I would expect that hedging this risk would be easier, not more difficult, than hedging risk with respect to other factors. Aside from the $PEAD$ factor and the factors in the DMRS model, the substantial risk reduction for all other arbitrage portfolios is a manifestation of strong post-formation correlations between the hedge portfolio excess return and the factor portfolio excess return (ρ), which range from 0.69 for the ROE factor in the Q model to 0.89 for the $SMB5$ factor in the FF5 model.

Finally, the results demonstrate that, as predicted, the hedge portfolios' net investment tends to be close to zero. The average sum of the hedge portfolio weights ($\overline{\sum w}$) ranges from -0.18 for the SMB factor in the FF model and the SMB^* factor in the DMRS model, to 0.06 for the MOM factor in the FFC model. Comparing these values to the sum of the absolute weights, which range from 0.83 for the CMA^* factor in the DMRS model to 1.89 for the ME factor in the Q model, the results demonstrate that the amounts invested on the long and short sides of the hedge portfolio are, on average, very similar. The results suggest that there is little need to constrain the hedge portfolio weights, since the unconstrained weights approximately satisfy the zero-net investment criterion and the performance of the arbitrage portfolios is as intended. In summary, the arbitrage portfolios are highly successful at profiting from the betting against beta effects evident in the US stock market.

5 International Stock Markets

Having demonstrated strong betting against beta effects for most, if not all, factors in the US stock market, I next investigate whether similar effects exist in international stock markets. I conduct the international stock market tests using stocks from two regions. The first is the Asia Pacific region, which includes stocks from Australia, Hong Kong, New Zealand, and Singapore. For simplicity I will refer to this region simply as "Asia". The second is the Europe region, which includes stocks from 16 European nations. The countries in each region, along with the major exchanges for each country and the primary currencies for each country, are shown in Table 5. I choose these regions because factor data for these regions are available from Ken French's website.[18] The countries I include in each region are the same as the countries whose stocks are used by Ken French to generate the factors for the given region.

5.1 Data

For each region, daily and monthly $MktRF$, SMB, HML, MOM, $SMB5$, CMA, and RMW factor excess returns for July 1990 through December 2018 are collected from Ken French's website. The factor returns are in US dollars. These factors enable me to conduct tests using the CAPM, FF, FFC, and FF5 models. Data for international versions of the factors in other models are unavailable. Daily stock price, shares outstanding, and exchange rate data, as well as data indicating issuing firms' locations, are collected from CompuStat Global. Because the international factor returns are US dollar returns, I convert all stock prices into US dollar prices and use these prices, along with adjustment factors that account for dividends and splits, to calculate daily and monthly stock returns. To ensure data quality, following Ince and Porter (2006) and Gao, Parsons, and Shen (2017), I impose two screens on the monthly return data. First, I drop stock-month observations where the return is in either the top or bottom 0.1% of monthly return observations for the given country, where the stock's country is defined as the country in which the headquarters of the firm issuing

[18] Ken French also provides factors for a Global region that includes all countries in his data set and a Global ex US region that includes all countries in his data set with the exception of the US. I do not examine these global regions because of empirical challenges arising from the fact that different stock markets are open at different times. The asynchronicity of the returns of stocks in different regions may impact the coefficients from time-series regressions of stock excess returns on factor excess returns, which are the basis of my analysis. These issues are less severe for countries that are geographically proximate, such as those in the regions I examine. Ken French also provides factors for a North America region that includes the US and Canada. I do not perform tests on the North America region because I have already examined the US market, which accounts for the majority of the stocks in the North America region.

the stock is located. Second, I identify stock i and month t observations where the return of the stock in month t or $t-1$ is greater than 300% but the compounded return over months $t-1$ and t is less than 50%, and remove the returns for stock i corresponding to both month $t-1$ and month t.

5.2 Factor Risk Premia

Table 6 summarizes the monthly excess returns for each factor in each region. As with the tests in the US market, the average excess return for each factor j serves as the estimate of the factor risk premium λ_j. The international stock analyses cover return months from January 1995 through December 2018, inclusive. In both Asia and Europe, the $MktRF$ factor has an economically large and positive but statistically insignificant average excess return. The average excess returns of the size factors, SMB and $SMB5$, are negative and insignficant in Asia and positive but small and insignificant in Europe. The average excess returns of the HML, MOM, CMA, and RMW factors in Asia are all positive, large, and highly significant. In Europe, the MOM and RMW factors generate large, positive, and significant average excess returns, but the average excess returns of the HML and CMA factors are smaller and insignificant. The small and sometimes negative premia on the size factors in Asia and the size, HML, and CMA factors in Europe make it unlikely that I will find stong betting against beta effects with respect to these factors.

5.3 Test Assets

The decile portfolio test assets used in the international market tests are constructed in the same manner as the test assets used in the analyses of the US market, with one exception. Because different exchanges within the same region have different closing times and holidays, by the time the pre-formation betas for some stocks could be calculated and used in the sorting procedure, the exchanges that other stocks trade on are closed, making it impossible to trade such stocks. To ensure that the portfolios examined are tradable, when forming portfolios at the end of month t, I sort stocks based on betas calculated using five years of monthly data as of the end of month $t-1$.[19]

To determine which stocks are included in the test assets formed at the end of month t for any given region, I start with all common stocks of firms headquartered in one of the

[19]In Section IA5 and Tables IA8-IA11 of the Internet Appendix, I show my conclusions are qualitatively unchanged if I use pre-formation betas estimated from 12 months of daily data, instead of five years of monthly data.

region's countries for which a month t price is available. I then follow Gao et al. (2017) and apply several filters. First, I remove stocks that are not the issuing firm's primary share class, stocks that trade in a currency that is not the primary currency for the country in which the issuing firm is headquartered, and stocks that are not listed on a major exchange for the country in which the firm issuing the stock is headquartered. I consider an exchange to be a major exchange for a country if, at the end of any month during the sample period, the total market capitalization of the given country's stocks that are listed on the exchange is 5% or more of the total market capitalization of the given country's stocks listed on all exchanges. Finally, to ensure data quality, I remove stock, month observatons that are in the bottom 5% of market capitalization or price among all stocks in the same country and in the same month.[20] Summary statistics for the pre-formation betas of the stocks included in the international analyses are presented in Section IA6 and Table IA12 of the Internet Appendix. In the average month, there are 2118 stocks in Asia and 4200 stocks in Europe.

Average monthly excess returns, post-formation betas, and alphas for each of the decile portfolios used in the international stock market tests, along with the associated $10-1$ portfolios, are shown in Table 7. To save space, for each portfolio, I present only the post-formation beta associated with the measure of pre-formation beta used to construct the portfolios. Full results for all decile portfolios are in Section IA7 and Table IA13 of the Internet Appendix. The results provide very little evidence of relations between betas and expected stock returns. In Asia, six of the $10-1$ portfolios have positive average excess returns, all of which are insignificant, while the other seven have negative average excess returns, three of which are significant and four of which are insignificant. Not surprisingly given the negative premia generated by the size factors in Asia (see Table 6), the three negative and significant $10-1$ portfolio average excess returns are for portfolios formed by sorting on size betas. In Europe, five of the $10-1$ portfolios generate positive but insignificant average excess returns, and the other eight $10-1$ portfolios generate negative and insignificant average excess returns.

As was the case in the US, the portfolio construction methodology successfully produces test assets with strong post-formation dispersion in risk factor exposure. In Asia, all of the $10-1$ portfolios have a positive post-formation beta corresponding to the pre-formation beta on which the portfolios were formed, 12 out of 13 of which are economically large and highly statistically significant. The results are even stronger in Europe, where all post-formation

[20]The requirement that each stock have at least 12 monthly return observations, used by Hou, Karolyi, and Kho (2011) and Gao et al. (2017), is enforced by the requirement that betas be estimated using at least 24 observations.

betas are positive and significant. For all sets of portfolios in both regions, examination of the individual decile portfolios' post-formation betas indicates an increasing, albeit not always monotonic, pattern in post-formation betas across the decile portfolios. The portfolios' large dispersion in post-formation factor exposures indicates that the factor models successfully capture several dimesions of commonality in international stock returns, and that stock-level betas with respect to the factors are persistent.

As expected, given that most of the $10-1$ portfolios have large post-formation risk exposures but small and insignificant average excess returns, the portfolios tend to generate negative alpha. In Asia, 12 of the 13 $10-1$ portfolios have negative alpha, four of which are significant. In Europe, nine of the 13 $10-1$ portfolios have negative alpha, but only one of these is significant. While preliminary, consistent with what was observed in the US market, the results suggest the existence of betting against beta effects for non-market factors in international stock markets.

5.4 Security Market Plane and Betting Against Beta

The focal international stock market bettting against beta tests are, as was the case in the US, cross-sectional regressions of average excess returns on post-formation portfolio betas. The results of the these regressions, shown in Table 8, indicate that betting against beta effects exist with respect to most, but not all, international market factors.[21]

In Asia, nine of the security market plane slope estimates, $\lambda-\psi$, are positive, but only those of the $MktRF$ and RMW factors in the FF5 model are significant. Of the four $\lambda-\psi$ values that are negative, three of these are significant. Consistent with the negative size factor risk premia and negative average excess return of the $10-1$ portfolios formed by sorting on size betas, the three significantly negative $\lambda-\psi$ estimates are for the size factors in the FF, FFC, and FF5 models. Thus, excluding the negative relations between size betas and expected returns, which are consistent with the negative premia earned by the size factors, the results suggest that in Asia, the security market plane is flat along most dimensions. Consistent with this notion, the estimated betting against beta effects, ψ, are all positive and most are statistically significant.

The results for Europe provide stronger evidence of relations between betas and expected stock returns than the results for the US and Asia. Nine of the 13 estimates of $\lambda-\psi$ in Europe are positive, and five of these are significant. Of the four negative $\lambda-\psi$ estimates,

[21] In Section IA8 and Table IA14 of the Internet Appendix, I show that the results are robust using an alternative methodology motived by Fama and MacBeth (1973).

only that of the $MktRF$ factor in the CAPM model is significant. Once again, all 13 Europe factors have positive estimates of ψ, six of which are significant. Three of the insignificant estimated values of ψ correspond to size factors, and are thus not surprising given the small and insignificant size factor premia. Three of the remaining four insignificant values of ψ correspond to factors for which the security market plane slope is significantly positive, and are thus also not surprising.

5.5 Aribtrage Portfolio Performance

I next examine the performance of international stock arbitrage portfolios. I construct arbitrage portfolios for each non-market factor in each region using the same methodology as was used to create the arbitrage portfolios for US stocks, with one exception. To account for different exchange closing times and calendars within a given region, I ensure that the weights used to construct the hedge portfolios can be calculated prior to the time at which trading would need to take place by excluding data from the last seven days in month t when running the regression used to calculate the hedge portfolios weights.[22]

Table 9 describes the performance and other characterstics of the international arbitrage portfolios. In Asia, the arbitrage portfolios for all factors other than the size factors generate significantly positive average excess returns. The fact that the size factor arbitrage portfolios do not generate significant average excess returns is expected given the negative premia and security market plane slopes associated with these factors. As was the case in the US market, the correlation between the average arbitrage portfolio excess returns and the betting against beta parameter (ψ, repeated from Table 8 to facilitate comparison) of 0.83 is quite high. Similarly, the correlation between the average arbitrage portfolio excess returns and the factor risk premia (λ, repeated from Table 6 to facilitate comparison) of 0.84 is also high. The arbitrage portfolios all have substantially less risk than the corresponding factors, a result of high post-formation correlation between the factors and hedge portfolios, which range from 0.62 for the SMB factor in the FF5 model to 0.78 for the RMW factor in the FF5 model. Finally, for all factors, the net investment of the hedge portfolio is small in magnitude compared to the corresponding sum of the absolute hedge portfolio weights.

The performance of the arbitrage portfolios in Europe is not as strong as that of the US and Asia region portfolios. While all arbitrage portfolios generate positive average excess

[22]In Section IA9 and Table IA15 of the Internet Appendix, I show that the results are extremely similar when using three or 12 months, instead of six months, of daily data to calculate the international hedge portfolio weights.

returns, only the 0.96% per month (t-statistic = 6.15) earned by the MOM factor arbitrage portfolio in the FFC model and the 0.33% per month (t-statistic = 4.51) earned by the RMW factor arbitrage portfolio in the $FF5$ model are significant. These results are exactly as expected given that the MOM and RMW factors are the only factors in Europe that generate a significant risk premium. The results are also consistent with the evidence that betas are more strongly related to expected stock returns in Europe than in the US or Asia. Despite the stronger relations between betas and expected returns, the correlation between the average arbitrage portfolio excess returns and estimates of the betting against beta effects (ψ, repeated from Table 8 to facilitate comparison) is 0.46, which, while smaller than the corresponding correlation for other regions, remains substantial. Perhaps more importantly, the correlation between the average arbitrage portfolio excess returns and the factor risk premia (λ, repeated from Table 6 to facilitate comparison) of 0.98 is extremely high. This suggests that if the factors themselves had generated higher and more significant average excess returns during the period studied, the average excess returns of the arbitrage portfolios may have been commensurately larger and more significant as well. Finally, consistent with the objective of the arbitrage portfolio design, in all cases the standard deviation of the monthly arbitrage portfolio excess returns is substantially lower than that of the corresponding factor, the correlation between the hedge portfolio excess return and the factor excess return is high, and the net investment of the hedge portfolios is, on average, close to zero.

To summarize, for all factors in Asia and Europe that generate significantly positive average excess returns, the corresponding arbitrage portfolio generates a similarly large, positive, and statistically significant average excess return with substantially reduced risk.

6 Drivers of Betting Against Beta Effects

The results in previous sections document strong betting against beta effects for most factors in most regions and that the arbitrage portfolios, which are designed to profit from these effects, earn large positive average excess returns. However, the results do not shed light on the drivers of these effects. In this section, I examine whether there is a common economic force that drives the betting against beta effects for different factors and regions, and whether previously-proposed explanations for the betting against market beta effect can explain these effects for non-market factors.

6.1 Arbitrage Portfolio Correlations

If the same economic force drives all of the betting against beta effects, the excess returns of the arbitrage portfolios for different factors and regions should have large positive correlations. Contrary to this prediction, the time-series correlations of arbitrage portfolio excess returns, shown in Table 10, are quite low. Panel A shows correlations across factors within each model and region. Most of the correlations are actually negative, and nearly all are below 0.1. The only substantial positive correlation is that between the HML and CMA factors' arbitrage portfolios, which ranges from 0.35 to 0.48 across the three regions. The results suggest that there is no single economic force that drives the betting against beta effects for different factors. Panel B of Table 10 shows correlations between the excess returns of the arbitrage portfolios for the same factor and factor model, but different regions. The correlations are all positive, but many are not large in magnitude. The results therefore provide weak evidence that, for a given factor, the same underlying force is driving the betting against beta effect in different regions.

6.2 Explanations for Betting Against Beta Effects

The low correlations between the arbitrage portfolio excess returns within each region make it unlikely that any of the previously-proposed explanations for the betting against market beta effect will explain the betting against beta effects on all other factors. Nonetheless, I proceed to examine whether previously-proposed explanations can account for these effects.

6.2.1 Leverage and Margin Constraints

FP propose that leverage and margin constraints drive the betting against market beta effect, and thus predict that the excess returns of a betting against beta portfolio should be high subsequent to periods of high leverage constraints and should have a negative correlation with contemporaneous changes in leverage constraints. Following FP, I use the TED spread as a proxy for funding constraints and test this hypothesis by regressing monthly arbitrage portfolio excess returns on the contemporaneous change in the TED spread (ΔTED_t) and the level of the TED spread at the end of the previous month (TED_{t-1}).[23] Since the TED spread data begin in January 1986, the regressions using US arbitrage portfolios begin in February 1986. As discussed in FP, if leverage constraints drive the betting against beta

[23] TED spread data are gathered from the FRED database of the Federal Reserve Bank of St. Louis: `https://fred.stlouisfed.org/series/TEDRATE`.

effects, the coefficient on ΔTED_t should be negative and the coefficient on TED_{t-1} should be positive. The results of these regressions, shown in Table 11, provide little support for this hypothesis. Of the 17 US arbitrage portfolios, only one has a significant positive coefficient on TED_{t-1} and none have a significant negative coefficient on ΔTED_t. Of the 18 arbitrage portfolio for Asia and Europe, none have positive coefficients on TED_{t-1} and only four have negative and significant coefficients on ΔTED_t.[24] Not a single arbitrage portfolio has significant coefficients on both TED_{t-1} and ΔTED_t with signs that are consistent with the predictions. In sum, the results do not support the hypothesis that the betting against beta effects for non-market factors are driven by leverage and margin constraints.

FP also create betting against market beta (BAB) factors that are designed to capture the profits associated with betting against market beta effects in different regions. If the betting against beta effects for non-market factors are driven by the same economic forces as the betting against market beta effects, then the returns of FP's BAB factors should be highly correlated with the returns of my arbitrage portfolios and the average excess returns of the arbitrage portfolios should be explained by this correlation. To test whether this is the case, I regress the arbitrage portfolio excess returns on the BAB factor excess returns. In the regressions for any given region, I use FP's BAB factor that region.[25] If the same force drives both the betting against market beta effect and betting against beta effect for other factors, then the intercept coefficient (alpha) from this regression should be insignificant and the slope coefficients should be large.

The results of these regressions, presented in Table 12, provide no evidence that the performance of the arbitrage portfolios can be explained by the BAB factors. In the US, the intercept coefficients (α) are all positive and statistically significant, and the slope coefficients (β^{BAB}), while mostly positive and sometimes significantly so, are small in magnitude. The results in Asia and Europe show that, of the arbitrage portfolios that generate significantly positive average excess returns (see Table 9), all have a significantly positive intercept from this regression. Furthermore, as was the case in the US, the estimated slope coefficients are all small in magnitude. The results therefore provide no evidence that the betting against market beta effects and betting against beta effects for non-market factors have a common driver.

[24] Contrary to their predictions, FP also find consistently negative coefficients on TED_{t-1} when running these tests using their betting against beta portfolios.

[25] BAB factor data are gathered from AQR's website: `https://www.aqr.com/Insights/Datasets/Betting-Against-Beta-Equity-Factors-Monthly`.

6.2.2 Lottery Demand

Bali et al. (2017) propose that lottery demand, which they measure using the average of the five highest daily returns of a given stock in the given month (MAX), explains the betting against beta anomaly. They find support for this hypothesis by demonstrating that including a lottery demand factor ($FMAX$) in their factor models explains the alpha of FP's betting against beta factor. To test whether lottery demand explains the average excess returns of the arbitrage portfolios, I regress the arbitrage portfolio excess returns on $FMAX$.[26] The results of these regressions, shown in Table 13, find little support for this prediction. In the US, all of the alphas are positive and highly significant. In Asia, all arbitrage portfolios that do not correspond to size factors have significantly positive alphas. The size factor arbitrage portfolios have insignificant average excess returns (see Table 9), thus the insignificant alphas for these factors cannot be seen as evidence that $FMAX$ explains a betting against size beta effect. Similarly, in Europe, all arbitrage portfolios that generated a significantly positive average excess return also generate significant positive alphas. Taken together, the results provide no evidence that lottery demand is the force behind all of the betting against beta effects.

6.2.3 Reference-Dependent Preferences and Mental Accounting

Finally, Wang et al. (2017) propose that reference-dependent preferences (RDP) combined with mental accounting (MA) drives the betting against market beta effect. RDP suggests that investors in loss regions are risk-seeking instead of risk-averse. MA suggests that investors apply these risk behaviors at the security level instead of the portfolio level. Accordingly, Wang et al. (2017) find that the betting against market beta effect is stronger among stocks whose owners are in the loss region on the given stock. They test this hypothesis by examining the strength of the betting against market beta anomaly among stocks with different levels of capital gains overhang (CGO), which measures the difference between the current price of a stock and the price at which the average current owner purchased the stock. If the combination of RDP and MA explains the betting against beta effects, then the effects should be stronger among stocks with low CGO, whose owners are in the loss region.

[26] Monthly $FMAX$ factor excess returns are gathered from Turan Bali's website: `https://sites.google.com/a/georgetown.edu/turan-bali/`. The $FMAX$ factor is the excess return of a portfolio that is long stocks with high MAX and short stocks with low MAX. Since there is a negative relation between MAX and future stock returns, the $FMAX$ factor has a negative average excess return. For consistency with the positive average excess return of other factors examined in this paper, I use the negative of the $FMAX$ factor as my version of the factor, but retain the same name for simplicity.

To test whether the combination of RDP and MA drive the betting against beta effects, following Wang et al. (2017), I examine whether the security market plane slopes are different among stocks with high and low CGO. Specifically, at the end of each month t, I sort stocks into quintiles based on an ascending ordering of CGO, calculated following Grinblatt and Han (2005).[27] I then sort stocks within each CGO quintile into decile portfolios based on a measure of beta, and calculate the month $t+1$ value-weighted excess return for each of the portfolios. The procedure is repeated for each measure of beta. For each resulting portfolio, I calculate the mean excess return and post-formation betas. Using only portfolios of stocks in the first and fifth quintiles of CGO, I then run a cross-sectional regression of average excess portfolio returns on post-formation betas and post-formation betas interacted with a high-CGO indicator. The regression specification is

$$\overline{r_p} = \Psi + \sum_{j \in \{M\}} \gamma_{1,j} \beta^j_{Post,p} + \sum_{j \in \{M\}} \gamma_{2,j} \beta^j_{Post,p} \times I_{HighCGO} + \epsilon_p \tag{17}$$

where $\overline{r_p}$ is the average excess return of portfolio p, $\beta^j_{Post,p}$ is the post-formation beta of portfolio p on factor j, $I_{HighCGO}$ is an indicator set to 1 for portfolios containing stocks in the top quintile of CGO, and $\{M\}$ is the set of all factors in factor model M. The regression is analogous to regression equation (6), except that it permits the security market plane slopes to differ among stocks with low and high values of CGO. Specifically, γ_1^j measures the security market plane slope along the β^j dimension for stocks in the first quintile of CGO, and thus is analogous to $\lambda_j - \psi_j$ in equation (6) for these stocks. γ_2^j measures the difference in this slope between stocks in the fifth and first quintiles of CGO. Since the risk premium, λ_j, applies to all stocks equally, γ_2^j measures the difference in the betting against beta effect, ψ_j, between low- and high-CGO stocks. Thus, if as predicted by Wang et al. (2017), the security market plane slope with respect to β^j is higher, and thus the betting against beta effect is smaller, for stocks in the fifth quintile of CGO compared to stocks in the first CGO quintile, I expect to see a positive estimate of γ_2^j.

The estimates of γ_2, shown in Table 14, provide little evidence that the combination of RDP and MA drive all of the betting against beta effects. In the US, consistent with the results in Wang et al. (2017), the estimate of γ_2 for the $MktRF$ factor using the CAPM model is significantly positive. However, only 13 of the 24 estimated γ_2 coefficients are positive, and only 8 are significantly so. Furthermore, five of the estimates of γ_2 are significantly negative. I find similar results in Asia and Europe. In both of these regions, the estimate of γ_2 for

[27] A complete description of the calculation of CGO is provided in Section IA10 of the Internet Appendix.

the $MktRF$ factor using the CAPM model is significantly positive. However, the results for other factor models give no indication that the observed betting against beta effects are consistently stronger among low-CGO stocks than among high-CGO stocks.

Overall, the results in this section provide no evidence that the betting against beta effects for different factors are driven by the same underlying force. Furthermore, previously-proposed explanations for the betting against market beta effect cannot explain the betting against beta effects for other factors.

7 Conclusion

In this paper, I present strong evidence of betting against beta effects for almost all factors in several established factor models in both the US and international stock markets. I form portfolios by sorting stocks on pre-formation measures of beta and examine the post-formation performance of these portfolios. The portfolios have strong post-formation dispersion in factor exposure, indicating that the factor models do a good job at capturing the factor structure of stock returns. Using the post-formation betas and average excess returns of these portfolios to estimate the security market plane slopes, I find little evidence that expected security returns are related to betas. The results indicate that the security market plane slopes are not only lower than the factor risk premia, but along almost all dimensions, the security market plane appears to be flat.

Motivated by APT, I then create "arbitrage portfolios" designed to profit from the betting against beta effects. The arbitrage portfolios take a long position in a factor portfolio and a short position in a hedge portfolio constructed to have unit exposure to the given factor and an expected excess return equal to the corresponding security market plane slope, which in most cases appears to be zero. The arbitrage portfolios generate average excess returns that are very similar to the factor risk premia with substantially reduced risk.

Finally, I examine whether the betting against beta effects all have a common driver and whether previously-proposed explanations of the betting against market beta anomaly can explain the the betting against beta effects for other factors. The correlations between the excess returns of the arbitrage portfolios are small for most pairs of factors, indicating that there is no single driver of all of the betting against beta effects. I also find that previously-proposed explanations for the betting against market beta effect cannot explain the betting against beta effects for other factors. Specifically, I find no evidence that leverage and margin constraints (FP), lottery demand (Bali et al. (2017)), or the combination of reference-dependent preferences and mental accounting (Wang et al. (2017)) drive the pricing patterns.

The results raise questions about the economic content of the factor models commonly used in the empirical asset pricing literature. The persistence of betas is strong evidence that these models successfully capture important dimensions of the covariance structure of stock returns. However, exposures to these risks are not related to expected stock returns. To reconcile these findings with the predictions of covariance-based models of expected security returns, one must argue that the sources of risk captured by the factor models are not priced, and that the models fail to capture dimensions of priced risk. This argument is difficult to reconcile with the high average excess returns earned by the factors. Furthermore, that my findings hold with respect to the factors in the DMRS model, which are designed explicitly to capture only the priced component of factors, makes this explanation even less likely to be true. Finally, it is highly improbable that after more than 50 years of research on expected stock returns that has uncovered hundreds of anomalies, this work has identified several dimensions of unpriced risk, but failed to identify the dimensions of risk that drive expected stock returns. The results, therefore, strongly suggest that covariance-based models of expected returns do not provide an accurate description of the market prices for securities.

References

Asness, C., Frazzini, A., Gormsen, N. J., and Pedersen, L. H. 2019. Betting against correlation: Testing theories of the low-risk effect. forthcoming, Journal of Financial Economics.

Bali, T. G., Brown, S. J., Murray, S., and Tang, Y. 2017. A lottery demand-based explanation of the beta anomaly. Journal of Financial and Quantitative Analysis, 52(6), 2369–2397.

Black, F. 1972. Capital market equilibrium with restricted borrowing. Journal of Business, 45(3), 444–455.

Black, F. 1993. Beta and return. Journal of Portfolio Management, 20(1), 8–18.

Black, F., Jensen, M. C., and Scholes, M. S. The capital asset pricing model: Some empirical tests. In M. C. Jensen, editor, *Studies in the Theory of Capital Markets*. Praeger, New York, 1972.

Brennan, M. J., Chordia, T., and Subrahmanyam, A. 1998. Alternative factor specifications, security characteristics, and the cross-section of expected stock returns. Journal of Financial Economics, 49(3), 345–373.

Carhart, M. M. 1997. On persistence in mutual fund performance. Journal of Finance, 52(1), 57–82.

Daniel, K., Hirshleifer, D., and Sun, L. 2019a. Short-and long-horizon behavioral factors. forthcoming, Review of Financial Studies.

Daniel, K., Mota, L., Rottke, S., and Santos, T. 2019b. The cross-section of risk and return. forthcoming, Review of Financial Studies.

Daniel, K. and Titman, S. 1997. Evidence on the characteristics of cross-sectional variation in stock returns. Journal of Finance, 52(1), 1–33.

Davis, J. L., Fama, E. F., and French, K. R. 2000. Characteristics, covariances, and average returns: 1929 to 1997. The Journal of Finance, 55(1), 389–406.

Fama, E. F. and French, K. R. 1992. The cross-section of expected stock returns. Journal of Finance, 47(2), 427–465.

Fama, E. F. and French, K. R. 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics, 33(1), 3–56.

Fama, E. F. and French, K. R. 2015. A five-factor asset pricing model. Journal of Financial Economics, 116(1), 1–22.

Fama, E. F. and MacBeth, J. D. 1973. Risk, return, and equilibrium: Empirical tests. Journal of Political Economy, 81(3), 607–636.

Frazzini, A. and Pedersen, L. H. 2014. Betting against beta. Journal of Financial Economics, 111(1), 1–25.

Gao, P., Parsons, C. A., and Shen, J. 2017. Global relation between financial distress and equity returns. The Review of Financial Studies, 31(1), 239–277.

Golubov, A. and Konstantinidi, T. 2019. Where is the risk in value? evidence from a market-to-book decomposition. The Journal of Finance, 74(6), 3135–3186.

Grinblatt, M. and Han, B. 2005. Prospect theory, mental accounting, and momentum. Journal of Financial Economics, 78(2), 311–339.

Hou, K., Karolyi, G. A., and Kho, B.-C. 2011. What factors drive global stock returns? The Review of Financial Studies, 24(8), 2527–2574.

Hou, K., Xue, C., and Zhang, L. 2015. Digesting anomalies: An investment approach. Review of Financial Studies, 28(3), 650–705.

Ince, O. S. and Porter, R. B. 2006. Individual equity return data from thomson datastream: Handle with care! Journal of Financial Research, 29(4), 463–479.

Jegadeesh, N. and Titman, S. 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. Journal of Finance, 48(1), 65–91.

Lewellen, J., Nagel, S., and Shanken, J. 2010. A skeptical appraisal of asset pricing tests. Journal of Financial economics, 96(2), 175–194.

Linnainmaa, J. T. and Roberts, M. R. 2018. The history of the cross-section of stock returns. The Review of Financial Studies, 31(7), 2606–2649.

McLean, R. D. and Pontiff, J. 2016. Does academic research destroy stock return predictability? Journal of Finance, 71(1), 5–32.

Newey, W. K. and West, K. D. 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica, 55(3), 703–708.

Novy-Marx, R. 2013. The other side of value: The gross profitability premium. Journal of Financial Economics, 108(1), 1–28.

Ross, S. A. 1976. The arbitrage theory of capital asset pricing. Journal of Economic Theory, 13(3), 341–360.

Stambaugh, R. F. and Yuan, Y. 2016. Mispricing factors. The Review of Financial Studies, 30(4), 1270–1315.

Towns, J., Cockerill, T., Dahan, M., Foster, I., Gaither, K., Grimshaw, A., Hazlewood, V., Lathrop, S., Lifka, D., Peterson, G. D., et al. 2014. XSEDE: accelerating scientific discovery. Computing in Science & Engineering, 16(5), 62–74.

Wang, H., Yan, J., and Yu, J. 2017. Reference-dependent preferences and the risk–return trade-off. Journal of Financial Economics, 123(2), 395–414.

Table 1: Factor Summary Statistics

This table presents summary statistics for the factors in each of the US factor models. The column labeled "Model" indicates the factor model or models from which the factors are taken. The CAPM model includes only the market factor ($MktRF$). The FF model includes $MktRF$ and the size (SMB) and book-to-market (HML) factors of Fama and French (1993). The FFC model follows Carhart (1997) and includes $MktRF$, SMB, HML, and a momentum factor (MOM) that captures the momentum effect documented by Jegadeesh and Titman (1993). The FF5 model includes $MktRF$, HML, and the size ($SMB5$), profitability (RMW), and investment (CMA) factors of Fama and French (2015). The Q model includes the market ($MKTQ$), size (ME), investment (IA), and profitability (ROE) factors of Hou et al. (2015). The SY model includes $MktRF$ and the size ($SMBSY$), management ($MGMT$), and performance ($PERF$) factors of Stambaugh and Yuan (2016). The DHS model includes $MktRF$ and the post-earnings announcement drift ($PEAD$) and financing (FIN) factors of Daniel et al. (2019a). The DMRS model includes the market ($MktRF^*$), size (SMB^*), value (HML^*), investment (CMA^*), and profitability (RMW^*) factors of Daniel et al. (2019b). The column labeled "Time Period" indicates the period for which the summary statistics for the factors in the given model are calculated. The column labeled "Factor" indicates the factor to which summary statistics in the given row pertain. The column labeled "λ" presents the time-series mean of the monthly factor excess returns. The column labeled "σ" presents the standard deviation of the monthly factor excess returns. The column labeled "$t(\lambda)$" presents the t-statistic, adjusted following Newey and West (1987) using 3 lags, testing the null hypothesis that the average factor excess return is equal to zero.

Model	Time Period	Factor	λ	σ	$t(\lambda)$
CAPM, FF, and FFC	196307-201812	$MktRF$	0.51	4.39	(2.90)
		SMB	0.21	3.06	(1.68)
		HML	0.32	2.80	(2.61)
		MOM	0.66	4.17	(4.06)
FF5	196807-201812	$MktRF$	0.49	4.50	(2.60)
		$SMB5$	0.15	3.02	(1.21)
		HML	0.33	2.88	(2.43)
		CMA	0.32	1.99	(3.48)
		RMW	0.28	2.23	(2.71)
Q	197201-201812	$MKTQ$	0.52	4.48	(2.64)
		ME	0.26	3.07	(1.95)
		IA	0.37	1.85	(4.39)
		ROE	0.54	2.55	(4.99)
SY	196801-201612	$MktRF$	0.49	4.54	(2.54)
		$SMBSY$	0.39	2.86	(3.23)
		$PERF$	0.65	3.87	(3.99)
		$MGMT$	0.66	2.87	(5.12)
DHS	197707-201812	$MktRF$	0.63	4.40	(3.09)
		$PEAD$	0.58	1.88	(7.02)
		FIN	0.67	3.85	(3.70)
DMRS	196807-201812	$MktRF^*$	0.50	3.12	(3.61)
		SMB^*	0.13	1.92	(1.63)
		HML^*	0.22	1.72	(2.62)
		CMA^*	0.23	1.23	(3.94)
		RMW^*	0.24	1.48	(3.74)

Table 2: Performance of Beta-Sorted Portfolios

This table presents the results of analyses of the returns of portfolios formed by sorting stocks based on pre-formation betas. At the end of each month t, all stocks in the sample are sorted into decile portfolios based on an ascending sort of the given beta variable. The beta of stock i in month t for factor j in model M is calculated as the slope coefficient on factor j from a regression of excess stock returns on the contemporaneous excess returns of all factors in model M using 60 months of monthly excess return data covering months $t-59$ through t, inclusive. The value-weighted average month $t+1$ excess return for each portfolio, as well as that of a portfolio that is long the 10th decile portfolio and short the first decile portfolio (the $10-1$ portfolio), are then calculated. The column labeled "Model" indicates the model used to calculate the betas. The column labeled "Sort Variable" indicates the variable used to form the portfolios. The column labeled "Value" indicates the value reported in the given row. Rows with "$\overline{r}$" in the Value column present the time-series average of the month $t+1$ excess portfolio returns. Rows with β^{j}_{Post} in the Value column present post-formation betas for the portfolio. Rows with α in the Value column present the alpha of the portfolio. Excess returns and alphas are reported in percent per month. The alphas and post-formation betas are calculated from a time-series regression of excess portfolio returns on excess factor returns using the factors in the given model. The alpha is the intercept coefficient from the regression. β^{j}_{Post} is the slope coefficient on factor j calculated using the given model. The columns labeled "1", ..., "10" present results for decile portfolios 1 through 10, respectively. The column labeled "10−1" presents results for the $10-1$ portfolio. The column labeled "$t(10-1)$" presents t-statistics testing the null hypothesis that the average excess return, post-formation beta, or alpha of the $10-1$ portfolio is equal to zero. t-statistics are adjusted following Newey and West (1987) using 3 lags.

Model	Sort Variable	Value	1	2	3	4	5	6	7	8	9	10	$10-1$	$t(10-1)$
CAPM	β^{MktRF}	$\overline{r}$	0.49	0.48	0.64	0.52	0.54	0.58	0.55	0.50	0.51	0.50	0.01	(0.04)
		β^{MktRF}_{Post}	0.57	0.66	0.76	0.86	0.96	1.07	1.20	1.32	1.47	1.77	1.20	(13.64)
		α	0.19	0.14	0.25	0.08	0.05	0.04	−0.07	−0.17	−0.24	−0.41	−0.60	(−2.55)
FF	β^{MktRF}	$\overline{r}$	0.58	0.55	0.50	0.68	0.53	0.50	0.58	0.53	0.49	0.58	0.00	(0.01)
		β^{MktRF}_{Post}	0.68	0.72	0.78	0.84	0.95	1.02	1.10	1.18	1.28	1.46	0.78	(12.38)
		β^{SMB}_{Post}	0.55	0.05	−0.12	−0.09	−0.13	−0.06	−0.04	0.02	0.12	0.45	−0.09	(−1.00)
		β^{HML}_{Post}	0.07	0.12	0.14	0.06	−0.04	0.03	0.12	0.14	0.07	−0.01	−0.08	(−0.81)
		α	0.09	0.13	0.07	0.25	0.09	−0.03	−0.02	−0.12	−0.21	−0.26	−0.35	(−2.01)
	β^{SMB}	$\overline{r}$	0.41	0.53	0.65	0.66	0.74	0.73	0.75	0.71	0.52	0.41	0.00	(0.01)
		β^{MktRF}_{Post}	0.95	0.95	0.98	1.04	1.09	1.14	1.16	1.20	1.26	1.30	0.35	(6.11)
		β^{SMB}_{Post}	−0.31	−0.10	0.05	0.21	0.37	0.51	0.67	0.83	1.03	1.44	1.75	(17.96)
		β^{HML}_{Post}	0.02	0.10	0.15	0.10	0.08	0.06	−0.01	0.04	−0.07	−0.24	−0.26	(−2.83)
		α	−0.02	0.03	0.09	0.06	0.08	0.02	0.02	−0.09	−0.31	−0.47	−0.45	(−3.05)
	β^{HML}	$\overline{r}$	0.50	0.51	0.36	0.55	0.50	0.55	0.62	0.67	0.85	0.66	0.16	(0.66)
		β^{MktRF}_{Post}	1.20	1.11	0.99	0.94	0.93	0.92	0.95	1.02	1.13	1.22	0.02	(0.32)
		β^{SMB}_{Post}	0.15	−0.06	−0.12	−0.10	−0.15	−0.09	−0.08	0.02	0.15	0.46	0.32	(4.40)
		β^{HML}_{Post}	−0.79	−0.46	−0.09	0.04	0.15	0.26	0.36	0.51	0.68	0.79	1.58	(17.48)
		α	0.11	0.10	−0.10	0.08	0.01	0.01	0.03	−0.03	0.02	−0.32	−0.43	(−2.42)

Table 2: Performance of Beta-Sorted Portfolios - continued

Model	Sort Variable	Value	1	2	3	4	5	6	7	8	9	10	10 − 1	$t(10-1)$
FFC	β^{MktRF}	$\bar{r}$	0.51	0.56	0.50	0.65	0.55	0.50	0.59	0.46	0.53	0.52	0.02	(0.07)
		β^{MktRF}_{Post}	0.77	0.72	0.81	0.84	0.95	1.00	1.07	1.15	1.23	1.41	0.65	(13.12)
		β^{SMB}_{Post}	0.61	0.06	−0.12	−0.13	−0.14	−0.07	−0.04	0.05	0.12	0.45	−0.15	(−2.04)
		β^{HML}_{Post}	0.16	0.19	0.18	0.03	−0.00	−0.04	0.07	0.14	−0.01	−0.11	−0.27	(−3.23)
		β^{MOM}_{Post}	0.18	0.05	0.01	0.05	0.05	−0.04	−0.05	−0.10	−0.14	−0.15	−0.32	(−4.76)
		α	−0.18	0.08	0.05	0.21	0.06	0.04	0.06	−0.12	−0.03	−0.16	0.02	(0.10)
	β^{SMB}	$\bar{r}$	0.42	0.55	0.55	0.61	0.75	0.78	0.74	0.73	0.51	0.40	−0.02	(−0.08)
		β^{MktRF}_{Post}	0.94	0.95	1.00	1.02	1.09	1.11	1.17	1.17	1.24	1.29	0.34	(6.66)
		β^{SMB}_{Post}	−0.31	−0.12	−0.01	0.21	0.32	0.57	0.64	0.83	1.02	1.39	1.70	(19.13)
		β^{HML}_{Post}	−0.01	0.05	0.11	0.12	0.06	0.06	0.02	−0.02	−0.09	−0.29	−0.28	(−3.74)
		β^{MOM}_{Post}	0.02	−0.04	−0.01	−0.02	−0.03	−0.01	−0.05	−0.02	−0.06	−0.03	−0.05	(−0.77)
		α	−0.01	0.10	0.01	0.02	0.12	0.08	0.03	−0.02	−0.26	−0.44	−0.43	(−2.98)
	β^{HML}	$\bar{r}$	0.60	0.53	0.44	0.54	0.50	0.50	0.60	0.68	0.79	0.64	0.05	(0.19)
		β^{MktRF}_{Post}	1.16	1.08	1.00	0.98	0.94	0.91	0.94	1.01	1.10	1.22	0.06	(1.15)
		β^{SMB}_{Post}	0.20	0.04	−0.11	−0.09	−0.15	−0.08	−0.10	−0.01	0.13	0.50	0.30	(2.89)
		β^{HML}_{Post}	−0.79	−0.53	−0.14	0.04	0.15	0.24	0.32	0.45	0.63	0.66	1.44	(14.04)
		β^{MOM}_{Post}	−0.10	−0.12	−0.07	0.01	−0.01	−0.01	0.01	0.02	−0.00	0.03	0.13	(1.47)
		α	0.28	0.22	0.05	0.03	0.00	−0.03	0.03	0.00	−0.00	−0.32	−0.61	(−3.17)
	β^{MOM}	$\bar{r}$	0.77	0.60	0.57	0.56	0.44	0.60	0.48	0.58	0.61	0.52	−0.25	(−1.29)
		β^{MktRF}_{Post}	1.22	1.11	1.02	0.98	0.97	0.97	0.96	0.97	1.02	1.14	−0.08	(−1.35)
		β^{SMB}_{Post}	0.73	0.21	0.08	0.01	−0.09	−0.12	−0.12	−0.13	−0.06	0.40	−0.33	(−4.68)
		β^{HML}_{Post}	0.02	0.18	0.26	0.21	0.12	0.05	0.01	−0.10	−0.19	−0.37	−0.39	(−4.39)
		β^{MOM}_{Post}	−0.21	−0.24	−0.16	−0.07	−0.06	−0.02	0.04	0.07	0.13	0.15	0.35	(4.67)
		α	0.13	0.08	0.06	0.03	−0.04	0.13	−0.02	0.10	0.07	−0.13	−0.26	(−1.35)
FF5	β^{MktRF}	$\bar{r}$	0.47	0.49	0.55	0.58	0.54	0.50	0.56	0.47	0.50	0.52	0.05	(0.26)
		β^{MktRF}_{Post}	0.74	0.78	0.77	0.87	0.94	1.03	1.07	1.14	1.24	1.40	0.65	(11.74)
		β^{SMB5}_{Post}	0.49	0.06	−0.07	−0.14	−0.13	−0.06	−0.01	0.06	0.16	0.38	−0.11	(−1.59)
		β^{HML}_{Post}	−0.09	0.09	0.02	0.08	−0.05	−0.00	0.06	0.12	0.16	0.03	0.12	(1.01)
		β^{CMA}_{Post}	−0.39	−0.38	−0.18	−0.05	0.14	0.11	0.08	0.14	0.01	−0.07	0.33	(1.82)
		β^{RMW}_{Post}	−0.62	−0.16	−0.15	0.07	0.12	0.11	0.14	0.12	0.08	−0.23	0.39	(3.19)
		α	0.35	0.23	0.28	0.14	0.03	−0.07	−0.05	−0.22	−0.21	−0.15	−0.50	(−2.84)
	β^{SMB5}	$\bar{r}$	0.40	0.52	0.63	0.63	0.71	0.64	0.65	0.65	0.51	0.31	−0.10	(−0.34)
		β^{MktRF}_{Post}	0.99	0.94	0.99	1.02	1.08	1.12	1.11	1.16	1.19	1.23	0.23	(5.40)
		β^{SMB5}_{Post}	−0.30	−0.10	0.05	0.26	0.36	0.46	0.64	0.75	0.94	1.21	1.51	(18.22)
		β^{HML}_{Post}	0.08	0.06	0.08	0.06	0.07	0.07	−0.00	0.05	−0.09	−0.22	−0.30	(−2.30)
		β^{CMA}_{Post}	−0.03	−0.02	0.11	0.04	0.04	−0.00	−0.06	−0.13	−0.10	−0.16	−0.13	(−0.86)
		β^{RMW}_{Post}	−0.04	0.08	0.21	0.11	0.11	0.07	−0.03	0.00	−0.24	−0.57	−0.53	(−6.45)
		α	−0.04	0.03	0.01	0.03	0.05	−0.03	0.03	−0.01	−0.09	−0.20	−0.16	(−1.20)
	β^{HML}	$\bar{r}$	0.48	0.57	0.52	0.48	0.53	0.53	0.52	0.60	0.64	0.56	0.07	(0.31)
		β^{MktRF}_{Post}	1.12	1.06	1.01	1.00	0.99	0.96	0.97	0.99	1.11	1.25	0.13	(2.02)
		β^{SMB5}_{Post}	0.34	0.01	−0.08	−0.09	−0.07	−0.04	−0.00	0.03	0.15	0.46	0.12	(1.56)
		β^{HML}_{Post}	−0.68	−0.43	−0.19	−0.09	−0.00	0.16	0.23	0.43	0.65	0.75	1.43	(11.89)
		β^{CMA}_{Post}	−0.23	0.18	0.08	0.08	0.13	0.04	0.07	−0.10	−0.28	−0.44	−0.21	(−1.22)
		β^{RMW}_{Post}	−0.74	−0.06	0.19	0.20	0.23	0.14	0.20	0.10	0.01	−0.27	0.47	(3.05)
		α	0.38	0.15	0.02	−0.06	−0.06	−0.04	−0.11	−0.04	−0.05	−0.16	−0.54	(−3.01)
	β^{CMA}	$\bar{r}$	0.55	0.45	0.57	0.54	0.44	0.54	0.57	0.54	0.50	0.43	−0.12	(−0.61)
		β^{MktRF}_{Post}	1.13	1.03	1.02	1.01	0.98	0.98	1.02	1.01	1.04	1.04	−0.09	(−1.33)
		β^{SMB5}_{Post}	0.36	0.03	−0.07	−0.07	−0.09	−0.07	−0.07	0.02	0.11	0.49	0.14	(1.09)
		β^{HML}_{Post}	0.12	0.20	0.19	0.17	0.08	0.02	−0.02	0.03	−0.07	−0.34	−0.46	(−2.38)
		β^{CMA}_{Post}	−0.83	−0.67	−0.40	−0.10	−0.09	0.16	0.33	0.29	0.44	0.54	1.37	(5.39)
		β^{RMW}_{Post}	−0.44	−0.39	−0.14	−0.05	−0.05	0.18	0.27	0.30	0.34	−0.20	0.24	(1.21)
		α	0.29	0.19	0.18	0.04	−0.01	−0.05	−0.09	−0.15	−0.24	−0.16	−0.45	(−2.03)
	β^{RMW}	$\bar{r}$	0.29	0.48	0.50	0.46	0.51	0.62	0.52	0.52	0.61	0.40	0.11	(0.46)
		β^{MktRF}_{Post}	1.18	1.12	1.06	1.01	1.00	0.96	0.95	1.00	1.03	1.08	−0.11	(−1.83)
		β^{SMB5}_{Post}	0.23	−0.00	−0.09	−0.00	−0.05	−0.09	−0.00	−0.02	0.04	0.46	0.23	(2.12)
		β^{HML}_{Post}	−0.32	0.05	0.16	0.15	0.10	0.01	0.03	0.02	0.01	−0.07	0.25	(1.68)
		β^{CMA}_{Post}	−0.28	−0.33	−0.21	−0.08	0.02	0.07	0.08	0.11	0.14	0.09	0.37	(1.95)
		β^{RMW}_{Post}	−1.29	−0.69	−0.32	0.01	0.07	0.13	0.26	0.31	0.41	0.23	1.52	(9.92)
		α	0.22	0.21	0.10	−0.06	−0.04	0.09	−0.06	−0.09	−0.07	−0.27	−0.49	(−2.51)

Table 2: Performance of Beta-Sorted Portfolios - continued

Model	Sort Variable	Value	1	2	3	4	5	6	7	8	9	10	$10-1$	$t(10-1)$
Q	β^{MKTQ}	$\bar{r}$	0.51	0.63	0.58	0.65	0.57	0.57	0.52	0.51	0.54	0.48	−0.04	(−0.18)
		β^{MKTQ}_{Post}	0.80	0.73	0.77	0.86	0.94	0.98	1.06	1.13	1.26	1.41	0.61	(10.89)
		β^{ME}_{Post}	0.51	0.22	−0.06	−0.07	−0.12	−0.05	−0.06	0.03	0.10	0.32	−0.19	(−1.93)
		β^{IA}_{Post}	−0.17	−0.07	−0.01	0.04	0.08	0.01	0.13	0.15	0.08	−0.04	0.13	(0.83)
		β^{ROE}_{Post}	−0.30	−0.04	−0.01	0.07	0.10	0.05	0.09	0.10	−0.05	−0.18	0.12	(0.87)
		α	0.20	0.25	0.21	0.17	0.03	0.05	−0.11	−0.19	−0.14	−0.22	−0.42	(−1.93)
	β^{ME}	$\bar{r}$	0.45	0.57	0.59	0.67	0.77	0.84	0.56	0.69	0.61	0.32	−0.13	(−0.43)
		β^{MKTQ}_{Post}	0.96	0.94	0.97	1.03	1.06	1.09	1.12	1.16	1.19	1.25	0.30	(5.42)
		β^{ME}_{Post}	−0.29	−0.13	0.01	0.16	0.35	0.43	0.59	0.69	0.84	1.10	1.38	(16.01)
		β^{IA}_{Post}	0.06	0.14	0.09	0.12	0.06	−0.04	−0.18	−0.26	−0.41	−0.67	−0.73	(−6.76)
		β^{ROE}_{Post}	−0.04	0.10	0.08	0.12	0.07	0.03	0.00	−0.07	−0.16	−0.50	−0.46	(−5.55)
		α	0.03	0.01	0.00	−0.02	0.07	0.16	−0.10	0.05	0.01	−0.09	−0.12	(−0.64)
	β^{IA}	$\bar{r}$	0.54	0.56	0.58	0.55	0.51	0.67	0.58	0.52	0.62	0.57	0.02	(0.09)
		β^{MKTQ}_{Post}	1.25	1.14	1.09	0.99	0.95	0.91	0.94	0.98	1.09	1.14	−0.11	(−1.58)
		β^{ME}_{Post}	0.19	−0.03	−0.04	−0.10	−0.03	−0.07	−0.12	−0.03	0.02	0.33	0.14	(1.30)
		β^{IA}_{Post}	−1.16	−0.75	−0.14	0.01	0.14	0.36	0.41	0.50	0.71	0.55	1.71	(10.49)
		β^{ROE}_{Post}	−0.28	−0.33	0.02	0.09	0.15	0.13	0.14	0.17	0.16	−0.02	0.26	(1.96)
		α	0.44	0.43	0.06	0.02	−0.11	0.01	−0.10	−0.25	−0.30	−0.30	−0.73	(−3.10)
	β^{ROE}	$\bar{r}$	0.44	0.64	0.49	0.64	0.46	0.62	0.59	0.50	0.64	0.52	0.07	(0.28)
		β^{MKTQ}_{Post}	1.26	1.22	1.07	1.02	0.99	1.01	0.97	0.99	0.99	1.02	−0.24	(−4.42)
		β^{ME}_{Post}	0.68	0.29	0.06	0.03	−0.04	−0.06	−0.09	−0.10	−0.15	0.08	−0.59	(−7.61)
		β^{IA}_{Post}	−0.16	0.07	0.11	0.14	0.22	0.19	0.09	0.09	−0.08	−0.54	−0.38	(−2.25)
		β^{ROE}_{Post}	−0.82	−0.59	−0.49	−0.17	−0.08	0.02	0.14	0.24	0.27	0.24	1.07	(9.88)
		α	0.12	0.23	0.15	0.15	−0.08	0.03	0.01	−0.15	0.05	0.04	−0.08	(−0.41)
SY	β^{MktRF}	$\bar{r}$	0.53	0.63	0.54	0.61	0.59	0.48	0.49	0.47	0.47	0.50	−0.03	(−0.15)
		β^{MktRF}_{Post}	0.85	0.82	0.83	0.87	0.95	1.01	1.06	1.12	1.17	1.25	0.40	(7.18)
		β^{SMBSY}_{Post}	0.51	0.07	−0.07	−0.05	−0.10	−0.10	−0.04	−0.00	0.12	0.41	−0.09	(−1.06)
		β^{PERF}_{Post}	−0.20	0.08	0.05	0.03	0.07	0.01	0.01	−0.04	−0.10	−0.16	0.04	(0.42)
		β^{MGMT}_{Post}	−0.32	0.05	0.11	0.17	0.11	0.01	0.06	0.07	−0.05	−0.39	−0.07	(−0.69)
		α	0.26	0.11	0.05	0.07	0.04	0.01	−0.07	−0.11	−0.05	0.09	−0.17	(−0.71)
	β^{SMBSY}	$\bar{r}$	0.45	0.58	0.54	0.63	0.66	0.60	0.70	0.64	0.51	0.20	−0.25	(−0.86)
		β^{MktRF}_{Post}	0.97	0.98	0.98	1.03	1.05	1.07	1.07	1.10	1.13	1.13	0.16	(2.80)
		β^{SMBSY}_{Post}	−0.31	−0.10	0.04	0.19	0.34	0.48	0.58	0.77	0.95	1.17	1.48	(9.47)
		β^{PERF}_{Post}	0.00	0.05	−0.02	−0.00	−0.02	−0.03	−0.04	−0.06	−0.15	−0.22	−0.22	(−3.51)
		β^{MGMT}_{Post}	0.08	0.11	0.08	0.12	−0.00	−0.06	−0.18	−0.27	−0.36	−0.68	−0.75	(−7.70)
		α	0.04	0.04	0.00	−0.02	0.03	−0.06	0.10	0.02	−0.09	−0.23	−0.26	(−1.49)
	β^{PERF}	$\bar{r}$	0.59	0.58	0.68	0.59	0.57	0.62	0.52	0.38	0.45	0.44	−0.15	(−0.70)
		β^{MktRF}_{Post}	1.17	1.12	1.06	0.99	0.98	0.99	0.98	0.98	1.05	1.06	−0.10	(−1.77)
		β^{SMBSY}_{Post}	0.50	0.23	0.06	0.02	0.03	−0.04	−0.07	−0.04	−0.15	−0.05	−0.55	(−7.56)
		β^{PERF}_{Post}	−0.53	−0.34	−0.28	−0.14	−0.05	0.01	0.06	0.15	0.21	0.11	0.64	(11.00)
		β^{MGMT}_{Post}	−0.00	0.31	0.28	0.22	0.20	0.18	0.12	0.07	−0.16	−0.59	−0.59	(−6.24)
		α	0.17	−0.04	0.12	0.04	−0.03	0.02	−0.05	−0.23	−0.04	0.26	0.08	(0.46)
	β^{MGMT}	$\bar{r}$	0.31	0.55	0.49	0.53	0.56	0.48	0.49	0.57	0.61	0.53	0.22	(0.75)
		β^{MktRF}_{Post}	1.21	1.06	1.02	1.03	0.99	1.00	0.98	0.98	1.00	1.10	−0.11	(−1.38)
		β^{SMBSY}_{Post}	0.27	0.09	−0.09	−0.07	−0.06	−0.09	−0.09	−0.04	0.04	0.46	0.19	(2.05)
		β^{PERF}_{Post}	−0.10	−0.06	−0.05	0.05	0.01	0.04	−0.00	−0.01	0.01	−0.01	0.09	(0.83)
		β^{MGMT}_{Post}	−0.97	−0.66	−0.35	−0.03	0.08	0.21	0.28	0.32	0.40	0.32	1.29	(8.77)
		α	0.31	0.47	0.28	0.04	0.03	−0.14	−0.14	−0.10	−0.17	−0.40	−0.71	(−2.67)

Table 2: Performance of Beta-Sorted Portfolios - continued

Model	Sort Variable	Value	1	2	3	4	5	6	7	8	9	10	$10-1$	$t(10-1)$
DHS	β^{MktRF}	$\overline{r}$	0.47	0.66	0.60	0.62	0.68	0.67	0.60	0.66	0.71	0.69	0.22	(0.70)
		β^{MktRF}_{Post}	0.61	0.68	0.79	0.86	0.96	1.02	1.12	1.19	1.31	1.50	0.90	(7.78)
		β^{PEAD}_{Post}	0.36	0.33	0.18	0.05	−0.04	−0.00	−0.13	−0.24	−0.19	−0.36	−0.72	(−2.70)
		β^{FIN}_{Post}	−0.82	−0.17	0.08	0.18	0.13	0.13	0.09	0.02	0.03	−0.22	0.60	(2.87)
		α	0.43	0.16	−0.05	−0.07	0.01	−0.05	−0.09	0.04	−0.02	0.10	−0.33	(−1.04)
	β^{PEAD}	$\overline{r}$	0.69	0.93	0.68	0.68	0.69	0.70	0.65	0.67	0.61	0.44	−0.25	(−1.09)
		β^{MktRF}_{Post}	1.21	1.14	1.09	1.02	1.02	0.99	0.95	0.99	1.02	1.10	−0.11	(−1.30)
		β^{PEAD}_{Post}	−0.10	−0.09	−0.13	−0.10	−0.09	−0.07	−0.00	0.05	0.06	0.09	0.19	(1.05)
		β^{FIN}_{Post}	−0.28	0.01	0.13	0.16	0.16	0.18	0.14	0.00	−0.20	−0.63	−0.35	(−2.52)
		α	0.19	0.26	−0.02	−0.01	−0.00	−0.00	−0.03	0.02	0.08	0.13	−0.05	(−0.22)
	β^{FIN}	$\overline{r}$	0.43	0.50	0.62	0.63	0.67	0.74	0.67	0.70	0.72	0.69	0.26	(0.73)
		β^{MktRF}_{Post}	1.16	1.09	1.08	1.00	1.01	1.00	0.98	0.98	1.08	1.20	0.04	(0.39)
		β^{PEAD}_{Post}	0.07	0.11	−0.00	0.03	0.01	0.02	0.06	0.01	−0.11	−0.19	−0.26	(−1.42)
		β^{FIN}_{Post}	−1.18	−0.83	−0.51	−0.34	−0.14	0.01	0.11	0.22	0.36	0.42	1.60	(12.12)
		α	0.46	0.32	0.29	0.22	0.13	0.10	−0.05	−0.07	−0.13	−0.24	−0.70	(−2.41)
DMRS	β^{MktRF^*}	$\overline{r}$	0.33	0.47	0.54	0.53	0.44	0.56	0.46	0.59	0.62	0.64	0.31	(1.46)
		$\beta^{MktRF^*}_{Post}$	0.60	0.70	0.72	0.87	0.88	0.92	0.97	0.93	1.00	0.98	0.38	(4.38)
		$\beta^{SMB^*}_{Post}$	0.93	0.53	0.33	0.35	0.36	0.38	0.42	0.53	0.67	1.05	0.12	(0.64)
		$\beta^{HML^*}_{Post}$	−0.88	−0.37	−0.36	−0.29	−0.21	−0.14	−0.07	−0.00	−0.06	−0.45	0.43	(2.28)
		$\beta^{CMA^*}_{Post}$	−0.35	−0.46	−0.26	−0.14	−0.28	−0.30	−0.32	−0.48	−0.52	−0.68	−0.33	(−1.42)
		$\beta^{RMW^*}_{Post}$	−1.25	−0.66	−0.52	−0.41	−0.31	−0.28	−0.30	−0.30	−0.46	−1.12	0.13	(0.60)
		α	0.48	0.39	0.39	0.24	0.13	0.21	0.08	0.23	0.27	0.53	0.05	(0.22)
	β^{SMB^*}	$\overline{r}$	0.55	0.52	0.55	0.61	0.50	0.59	0.64	0.67	0.46	0.29	−0.25	(−0.90)
		$\beta^{MktRF^*}_{Post}$	0.87	0.85	0.87	0.87	0.94	0.94	0.95	0.90	0.90	0.93	0.06	(0.49)
		$\beta^{SMB^*}_{Post}$	0.15	0.28	0.45	0.61	0.80	0.96	1.21	1.35	1.69	1.86	1.71	(10.30)
		$\beta^{HML^*}_{Post}$	−0.49	−0.21	−0.12	−0.04	−0.12	−0.11	−0.26	−0.39	−0.54	−0.91	−0.42	(−1.58)
		$\beta^{CMA^*}_{Post}$	0.04	−0.19	−0.39	−0.54	−0.52	−0.63	−0.50	−0.52	−0.62	−0.49	−0.53	(−1.83)
		$\beta^{RMW^*}_{Post}$	−0.45	−0.30	−0.34	−0.45	−0.53	−0.52	−0.71	−0.85	−1.15	−1.59	−1.14	(−3.74)
		α	0.30	0.21	0.25	0.33	0.20	0.29	0.35	0.45	0.32	0.27	−0.03	(−0.09)
	β^{HML^*}	$\overline{r}$	0.45	0.55	0.45	0.52	0.45	0.51	0.60	0.63	0.71	0.48	0.03	(0.12)
		$\beta^{MktRF^*}_{Post}$	0.74	0.78	0.82	0.86	0.90	0.90	0.90	0.89	0.96	1.05	0.31	(2.30)
		$\beta^{SMB^*}_{Post}$	0.84	0.53	0.48	0.37	0.37	0.33	0.44	0.51	0.60	0.98	0.14	(0.93)
		$\beta^{HML^*}_{Post}$	−1.39	−1.04	−0.62	−0.32	−0.34	−0.12	0.07	0.26	0.34	0.33	1.72	(6.04)
		$\beta^{CMA^*}_{Post}$	−0.40	−0.18	−0.29	−0.24	−0.24	−0.26	−0.36	−0.41	−0.37	−0.70	−0.31	(−1.18)
		$\beta^{RMW^*}_{Post}$	−1.60	−0.88	−0.60	−0.42	−0.38	−0.23	−0.19	−0.21	−0.19	−0.66	0.94	(2.75)
		α	0.74	0.56	0.31	0.26	0.17	0.15	0.20	0.20	0.20	0.07	−0.67	(−2.34)
	β^{CMA^*}	$\overline{r}$	0.41	0.55	0.53	0.56	0.60	0.58	0.46	0.51	0.48	0.62	0.22	(1.06)
		$\beta^{MktRF^*}_{Post}$	0.89	0.92	0.81	0.89	0.87	0.92	0.88	0.88	0.87	0.67	−0.23	(−2.37)
		$\beta^{SMB^*}_{Post}$	0.88	0.62	0.45	0.46	0.40	0.40	0.41	0.43	0.58	1.01	0.13	(0.89)
		$\beta^{HML^*}_{Post}$	−0.41	−0.04	−0.08	−0.02	−0.11	−0.20	−0.25	−0.34	−0.63	−1.08	−0.68	(−3.27)
		$\beta^{CMA^*}_{Post}$	−0.91	−0.81	−0.75	−0.57	−0.33	−0.16	−0.10	0.10	0.09	0.12	1.03	(3.97)
		$\beta^{RMW^*}_{Post}$	−1.00	−0.51	−0.40	−0.33	−0.34	−0.35	−0.29	−0.37	−0.72	−1.31	−0.31	(−1.26)
		α	0.37	0.32	0.35	0.26	0.29	0.23	0.11	0.16	0.26	0.68	0.31	(1.27)
	β^{RMW^*}	$\overline{r}$	0.38	0.55	0.53	0.52	0.52	0.51	0.59	0.50	0.59	0.48	0.09	(0.42)
		$\beta^{MktRF^*}_{Post}$	0.84	0.84	0.81	0.91	0.90	0.90	0.87	0.87	0.91	0.95	0.10	(0.99)
		$\beta^{SMB^*}_{Post}$	0.71	0.62	0.55	0.41	0.39	0.45	0.38	0.41	0.46	0.85	0.14	(1.00)
		$\beta^{HML^*}_{Post}$	−1.21	−0.68	−0.43	−0.13	−0.17	−0.15	−0.12	−0.08	−0.01	−0.19	1.02	(4.47)
		$\beta^{CMA^*}_{Post}$	−0.51	−0.43	−0.43	−0.40	−0.44	−0.24	−0.38	−0.27	−0.28	−0.24	0.27	(1.40)
		$\beta^{RMW^*}_{Post}$	−2.05	−1.04	−0.76	−0.38	−0.38	−0.28	−0.26	−0.18	−0.24	−0.31	1.75	(6.70)
		α	0.73	0.54	0.42	0.22	0.24	0.15	0.27	0.14	0.19	0.06	−0.68	(−2.80)

Table 3: Security Market Plane and Betting Against Beta

This table presents estimates of the slopes of the security market plane and betting against beta effects with respect to betas on different factors using different factor models. The estimates of the security market plane slopes ($\lambda - \psi$) are calculated by regressing average portfolio excess returns on post-formation portfolio betas. The regression specification is $\overline{r_p} = \gamma + \sum_{j=1}^{n}(\lambda - \psi)^j \beta_{Post}^j + \epsilon_p$. The values of $\overline{r_p}$ and β_{Post}^f used in the regression are those of the decile portfolios reported in Table 2 for the given factor model. The estimates of the betting against beta effects (ψ) are calculated by taking the difference between the estimate of λ from Table 1 and the estimate of $\lambda - \psi$. The column labeled "Model" indicates the model used in the analysis. The column labeled "Factor" indicates the factor to which the values in the given row pertain. The column labeled "$\lambda - \psi$" presents the coefficient on β_{Post}^j from the regression. The column labeled "$t(\lambda - \psi)$" presents the t-statistic testing the null hypothesis that the slope coefficient, $\lambda - \psi$, is equal to zero. The column labeled "ψ" presents the estimates of ψ. The column labeled "$t(\psi)$" presents the t-statistic testing the null hypothesis that ψ is equal to zero, calculated by dividing ψ by the standard error of the estimate of $\lambda - \psi$.

Model	Factor	$\lambda - \psi$	$t(\lambda - \psi)$	ψ	$t(\psi)$
CAPM	$MktRF$	−0.02	(−0.42)	0.53	(11.67)
FF	$MktRF$	0.03	(0.28)	0.48	(3.92)
	SMB	0.06	(1.18)	0.14	(2.62)
	HML	0.20	(3.19)	0.12	(1.88)
FFC	$MktRF$	0.13	(0.74)	0.39	(2.26)
	SMB	0.05	(0.82)	0.16	(2.89)
	HML	0.13	(2.16)	0.19	(3.12)
	MOM	0.02	(0.10)	0.64	(2.95)
FF5	$MktRF$	0.00	(0.03)	0.49	(4.92)
	$SMB5$	0.04	(0.99)	0.11	(2.79)
	HML	0.03	(0.51)	0.30	(4.79)
	CMA	−0.11	(−1.55)	0.43	(6.21)
	RMW	0.19	(3.48)	0.09	(1.62)
Q	$MKTQ$	−0.07	(−0.61)	0.59	(4.96)
	ME	0.07	(1.21)	0.18	(3.03)
	IA	0.03	(0.55)	0.34	(7.41)
	ROE	0.14	(1.91)	0.40	(5.27)
SY	$MktRF$	−0.22	(−1.21)	0.71	(3.97)
	$SMBSY$	0.04	(0.75)	0.34	(6.10)
	$PERF$	−0.11	(−0.89)	0.76	(5.93)
	$MGMT$	0.16	(3.06)	0.50	(9.47)
DHS	$MktRF$	0.18	(0.77)	0.44	(1.89)
	$PEAD$	0.09	(0.30)	0.49	(1.64)
	FIN	0.19	(3.24)	0.48	(8.00)
DMRS	$MktRF^*$	−0.03	(−0.18)	0.54	(2.93)
	SMB^*	0.02	(0.39)	0.11	(2.28)
	HML^*	0.12	(1.27)	0.10	(1.06)
	CMA^*	0.05	(0.66)	0.18	(2.39)
	RMW^*	0.00	(0.03)	0.23	(2.74)

Table 4: Arbitrage Portfolios

This table describes the performance of arbitrage portfolios for non-market factors. The arbitrage portfolios are constructed by taking a long position in the factor portfolio and a short position in a hedge portfolio. The hedge portfolio combines decile portfolios formed by sorting on β^j in a manner intended to create a portfolio whose excess returns track, as closely as possible, the excess returns of the factor portfolio. The objective of the arbitrage portfolio is to profit from the given factor's betting against beta effect while taking as little risk as possible. Details of the construction of the arbitrage portfolios are in Section 4. The excess return of the arbitrage portfolio is taken to be the excess factor return minus the excess return of the hedge portfolio. The columns labeled "Model" and "Factor" indicate the factor model and factor, respectively, to which results in the given row pertain. The columns labeled "$\overline{r^{Arb}}$" and "$t(\overline{r^{Arb}})$" present the mean monthly excess return of the arbitrage portfolio and the t-statistic, adjusted following Newey and West (1987) using 3 lags, testing the null hypothesis that the mean arbitrage portfolio excess return is equal to zero. The columns labeled "ψ" and "λ" present the estimate of the betting against beta effect for the factor and the average factor excess return, respectively. The columns labeled σ^{Factor} and σ^{Arb} present the standard deviations of the monthly factor and arbitrage portfolio excess returns, respectively. The column labeled ρ shows the correlation between the factor excess returns and the hedge portfolio excess returns. The column labeled "$\overline{\sum w}$" presents the time-series average of the monthly sum of the weights of the decile portfolios in the hedge portfolio. The column labeled "$\overline{\sum |w|}$" presents the time-series average of the monthly sum of absolute values of the weights of the decile portfolios in the hedge portfolio.

Model	Factor	$\overline{r^{Arb}}$	$t(\overline{r^{Arb}})$	ψ	λ	σ^{Factor}	σ^{Arb}	ρ	$\overline{\sum w}$	$\overline{\sum \lvert w \rvert}$
FF	SMB	0.20	(3.28)	0.14	0.21	3.06	1.49	0.88	−0.18	1.78
	HML	0.26	(3.86)	0.12	0.32	2.80	1.59	0.83	−0.10	1.40
FFC	SMB	0.18	(2.92)	0.16	0.21	3.06	1.48	0.88	−0.17	1.79
	HML	0.26	(3.53)	0.19	0.32	2.80	1.66	0.81	−0.09	1.41
	MOM	0.58	(5.14)	0.64	0.66	4.17	2.98	0.70	0.06	1.82
FF5	$SMB5$	0.21	(3.49)	0.11	0.15	3.02	1.39	0.89	−0.17	1.87
	HML	0.30	(3.57)	0.30	0.33	2.88	1.74	0.81	−0.12	1.43
	CMA	0.33	(5.32)	0.43	0.32	1.99	1.34	0.74	−0.06	1.15
	RMW	0.25	(3.70)	0.09	0.28	2.23	1.50	0.74	0.02	1.10
Q	ME	0.21	(3.02)	0.18	0.26	3.07	1.58	0.86	−0.15	1.89
	IA	0.36	(6.59)	0.34	0.37	1.85	1.23	0.75	−0.03	1.05
	ROE	0.53	(6.52)	0.40	0.54	2.55	1.86	0.69	0.05	1.21
SY	$SMBSY$	0.37	(5.46)	0.34	0.39	2.86	1.52	0.85	−0.17	1.84
	$PERF$	0.62	(5.71)	0.76	0.65	3.87	2.54	0.75	−0.00	1.86
	$MGMT$	0.55	(7.78)	0.50	0.66	2.87	1.55	0.84	−0.11	1.43
DHS	$PEAD$	0.57	(7.09)	0.49	0.58	1.88	1.83	0.30	0.02	1.10
	FIN	0.65	(6.65)	0.48	0.67	3.85	2.07	0.84	−0.15	1.74
DMRS	SMB^*	0.23	(3.58)	0.11	0.13	1.92	1.57	0.58	−0.18	1.25
	HML^*	0.28	(3.84)	0.10	0.22	1.72	1.46	0.52	−0.04	1.06
	CMA^*	0.23	(4.28)	0.18	0.23	1.23	1.16	0.36	−0.02	0.83
	RMW^*	0.20	(3.40)	0.23	0.24	1.48	1.36	0.39	0.04	0.87

Table 5: International Regions

This table shows the countries included in the Asia (Panel A) and Europe (Panel B) regions. For each country, the table presents the country's major stock exchanges, the country's primary currencies, and, where applicable to the 199501-201812 time period covered by the international stock market analyses, the time when each primary currency ceased or began to be the primary currency for the country.

Panel A: Asia

Country	Major Exchanges	Primary Currencies
Australia	Australian Stock Exchange	Australian Dollar
Hong Kong	Hong Kong Stock Exchange	Hong Kong Dollar
New Zealand	Wellington Stock Exchange	New Zealand Dollar
Singapore	Singapore Stock Exchange	Singapore Dollar

Panel B: Europe

Country	Major Exchanges	Primary Currencies
Austria	Vienna Stock Exchange	Austrian Schilling through December 1998
		Euro beginning in January 1999
Belgium	NYSE Euronext Brussels	Belgian Franc through December 1998
	Berlin Stock Exchange	Euro beginning in January 1999
Denmark	Copenhagen Stock Exchange	Danish Kroner
Finland	Helsinki Stock Exchange	Finnish Markka through December 1998
		Euro beginning in January 1999
France	Paris Stock Exchange	French Franc through December 1998
	NYSE Euronext Paris	Euro beginning in January 1999
Germany	Frankfurt Stock Exchange	Deutsche Mark through December 1998
	IBIS	Euro beginning in January 1999
Great Britain	London Stock Exchange	British Pound
Greece	Athens Stock Exchange	Greek Drachma through December 2000
		Euro beginning in January 2001
Ireland	Irish Stock Exchange	Irish Pound through December 1998
	Frankfurt Stock Exchange	Euro beginning in January 1999
	London Stock Exchange	
Italy	Milan Stock Exchange	Italian Lira through December 1998
		Euro beginning in January 1999
Netherlands	NYSE Euronext Amsterdam	Dutch Guilder through December 1998
	NYSE Euronext Paris	Euro beginning in January 1999
Norway	Oslo Stock Exchange	Norwegian Kroner
Portugal	Lisbon Stock Exchange	Portuguese Escudo through December 1998
		Euro beginning in January 1999
Spain	Madrid Stock Exchange	Spanish Peseta through December 1998
		Euro beginning in January 1999
Sweden	Stockholm Stock Exchange	Swedish Krona
Switzerland	SWX Stock Exchange	Swiss Franc
	Zurich Stock Exchange	

Table 6: Factor Summary Statistics - International

This table presents summary statistics for the international factors in the CAPM, FF, FFC, and FF5 factor models. Panel A presents results for Asia and Panel B presents results for Europe. The analyses cover the months from January 1995 through December 2018, inclusive. The columns labeled "Factor" indicate the factor to which summary statistics in the given row pertain. The columns labeled "λ" present the time-series means of the monthly factor excess returns. The columns labeled "σ" present the standard deviations of the monthly excess factor returns. The columns labeled "$t(\lambda)$" present the t-statistic, adjusted following Newey and West (1987) using 3 lags, testing the null hypothesis that the average factor excess returns are equal to zero.

Panel A: Asia

Factor	λ	σ	$t(\lambda)$
$MktRF$	0.59	5.86	(1.52)
SMB	−0.26	3.00	(−1.36)
HML	0.62	3.12	(3.47)
MOM	0.76	4.59	(2.47)
$SMB5$	−0.12	2.96	(−0.64)
CMA	0.38	2.36	(2.47)
RMW	0.32	2.81	(1.99)

Panel B: Europe

Factor	λ	σ	$t(\lambda)$
$MktRF$	0.52	4.94	(1.60)
SMB	0.05	2.20	(0.37)
HML	0.32	2.53	(1.65)
MOM	0.94	4.13	(3.45)
$SMB5$	0.11	2.15	(0.88)
CMA	0.16	1.91	(1.10)
RMW	0.35	1.61	(3.48)

Table 7: Performance of Beta-Sorted Portfolios - International

This table presents the results of analyses of the returns of portfolios formed by sorting stocks based on pre-formation betas in international stock markets. Panel A presents results for Asia and Panel B presents results for Europe. At the end of each month t, all stocks in the sample are sorted into decile portfolios based on an ascending sort of the given beta variable. The value-weighted average month $t+1$ excess return for each portfolio, as well as that of a portfolio that is long the 10th decile portfolio and short the first decile portfolio (the $10-1$ portfolio), are then calculated. The column labeled "Model" indicates the model used to calculate the betas. The column labeled "Sort Variable" indicates the variable used to form the portfolios. The column labeled "Value" indicates the value reported in the given row. Rows with "$\overline{r}$" in the Value column present the time-series average of the month $t+1$ excess portfolio returns. Rows with β^{j}_{Post} in the Value column present post-formation betas for the portfolio. Rows with α in the Value column present the alpha of the portfolio. Excess returns and alphas are reported in percent per month. The alphas and post-formation betas are calculated from a time-series regression of excess portfolio returns on excess factor returns using the factors in the given model. The alpha is the intercept coefficient from the regression. β^{j}_{Post} is the slope coefficient on factor j calculated using the given model. The columns labeled "1", ..., "10" present results for decile portfolios 1 through 10, respectively. The column labeled "10−1" presents results for the $10-1$ portfolio. The column labeled "$t(10-1)$" presents t-statistics testing the null hypothesis that the average excess return, post-formation beta, or alpha of the $10-1$ portfolio is equal to zero. t-statistics are adjusted following Newey and West (1987) using 3 lags.

Panel A: Asia

Model	Sort Variable	Value	1	2	3	4	5	6	7	8	9	10	10 − 1	t(10 − 1)
CAPM	β^{MktRF}	$\overline{r}$	0.57	0.32	0.80	0.69	0.69	0.72	0.71	0.49	0.60	0.62	0.05	(0.09)
		β^{MktRF}_{Post}	0.51	0.69	0.78	0.80	0.95	1.01	1.09	1.24	1.44	1.58	1.08	(14.03)
		α	0.27	−0.09	0.35	0.22	0.13	0.13	0.07	−0.24	−0.25	−0.31	−0.58	(−1.79)
FF	β^{MktRF}	$\overline{r}$	0.39	0.70	0.55	0.79	0.68	0.65	0.50	0.79	0.54	0.42	0.03	(0.05)
		β^{MktRF}_{Post}	0.49	0.64	0.70	0.83	0.90	1.06	1.16	1.19	1.40	1.52	1.03	(12.74)
		α	0.10	0.41	0.24	0.36	0.26	0.02	−0.32	−0.23	−0.56	−0.72	−0.82	(−2.07)
	β^{SMB}	$\overline{r}$	0.67	0.59	0.47	0.79	0.79	1.08	0.34	0.40	0.35	−0.74	−1.42	(−2.79)
		β^{SMB}_{Post}	−0.26	−0.16	−0.07	0.09	0.29	0.47	0.61	0.78	1.09	1.29	1.55	(11.71)
		α	−0.07	0.05	−0.05	0.24	0.21	0.51	−0.31	−0.21	−0.40	−1.45	−1.39	(−4.00)
	β^{HML}	$\overline{r}$	0.40	0.47	0.60	0.74	0.78	0.62	0.74	0.62	0.81	0.40	−0.00	(−0.01)
		β^{HML}_{Post}	−0.62	−0.41	−0.39	−0.25	0.01	0.27	0.56	0.60	0.89	0.86	1.48	(6.05)
		α	0.24	0.11	0.29	0.40	0.32	−0.13	−0.19	−0.44	−0.47	−0.77	−1.01	(−2.55)
FFC	β^{MktRF}	$\overline{r}$	0.31	0.75	0.57	0.78	0.57	0.72	0.47	0.88	0.47	0.46	0.15	(0.26)
		β^{MktRF}_{Post}	0.56	0.66	0.73	0.83	0.93	1.04	1.13	1.17	1.37	1.48	0.92	(15.94)
		α	−0.14	0.38	0.20	0.33	0.09	0.05	−0.25	0.03	−0.49	−0.25	−0.11	(−0.28)
	β^{SMB}	$\overline{r}$	0.72	0.50	0.51	0.63	0.95	0.76	0.58	0.22	0.28	−0.67	−1.39	(−2.77)
		β^{SMB}_{Post}	−0.25	−0.14	−0.09	0.13	0.19	0.49	0.53	0.85	1.08	1.30	1.55	(11.62)
		α	0.00	−0.10	−0.07	0.15	0.45	0.17	0.08	−0.44	−0.60	−1.35	−1.35	(−3.26)
	β^{HML}	$\overline{r}$	0.45	0.46	0.64	0.79	0.65	0.65	0.62	0.69	0.76	0.30	−0.16	(−0.34)
		β^{HML}_{Post}	−0.44	−0.42	−0.35	−0.25	0.03	0.18	0.42	0.62	0.87	0.76	1.21	(6.04)
		α	0.08	0.08	0.26	0.39	0.21	0.02	−0.21	−0.27	−0.37	−0.71	−0.78	(−1.60)
	β^{MOM}	$\overline{r}$	0.50	0.66	0.72	0.65	0.58	0.77	0.51	0.71	0.33	−0.09	−0.59	(−1.57)
		β^{MOM}_{Post}	−0.15	−0.16	−0.25	0.11	−0.02	0.06	0.10	0.08	0.07	0.04	0.18	(1.68)
		α	−0.30	−0.14	0.04	−0.14	−0.05	0.23	−0.04	0.19	−0.32	−0.55	−0.26	(−0.68)
FF5	β^{MktRF}	$\overline{r}$	0.05	0.56	0.45	0.74	0.69	0.53	0.70	0.81	0.64	0.05	0.00	(0.01)
		β^{MktRF}_{Post}	0.67	0.62	0.83	0.91	0.91	0.99	1.09	1.11	1.17	1.29	0.62	(6.95)
		α	−0.18	0.08	−0.15	0.05	0.08	−0.07	−0.01	0.15	0.13	−0.29	−0.11	(−0.33)
	β^{SMB5}	$\overline{r}$	0.62	0.58	0.66	0.81	0.52	0.88	0.85	0.47	0.19	−0.74	−1.36	(−2.59)
		β^{SMB5}_{Post}	−0.33	−0.10	0.04	0.16	0.19	0.35	0.60	0.74	1.01	1.00	1.33	(9.17)
		α	0.11	−0.05	0.02	0.04	−0.15	0.34	0.49	0.20	−0.01	−0.56	−0.67	(−1.67)
	β^{HML}	$\overline{r}$	0.45	−0.09	0.58	0.57	0.80	0.67	0.84	0.64	0.86	0.36	−0.09	(−0.21)
		β^{HML}_{Post}	−0.76	−0.11	−0.08	−0.13	0.06	0.16	0.09	0.56	0.34	0.11	0.87	(3.08)
		α	0.77	−0.36	0.17	0.08	0.13	−0.14	0.21	−0.26	0.25	0.13	−0.64	(−1.18)
	β^{CMA}	$\overline{r}$	0.26	0.77	0.71	0.52	0.56	0.39	0.74	0.61	0.79	0.46	0.20	(0.50)
		β^{CMA}_{Post}	−0.82	−0.37	−0.19	−0.19	−0.03	−0.13	0.13	0.15	0.22	0.08	0.90	(3.14)
		α	−0.16	−0.04	0.06	−0.04	−0.07	−0.01	0.16	0.04	0.30	−0.05	0.11	(0.22)
	β^{RMW}	$\overline{r}$	−0.10	0.47	0.63	0.79	0.63	0.41	0.68	0.69	0.87	0.35	0.45	(1.19)
		β^{RMW}_{Post}	−0.90	−0.95	−0.52	−0.25	−0.26	0.03	0.40	0.37	0.67	0.16	1.06	(5.32)
		α	−0.07	0.19	0.09	0.23	0.15	−0.20	0.06	−0.00	−0.03	−0.25	−0.19	(−0.50)

Table 7: Performance of Beta-Sorted Portfolios - International - continued

Panel B: Europe

Model	Sort Variable	Value	1	2	3	4	5	6	7	8	9	10	$10-1$	$t(10-1)$
CAPM	β^{MktRF}	$\overline{r}$	0.58	0.55	0.71	0.69	0.67	0.63	0.57	0.48	0.43	0.38	−0.20	(−0.52)
		β^{MktRF}_{Post}	0.54	0.57	0.71	0.77	0.87	0.94	1.07	1.14	1.31	1.51	0.97	(15.47)
		α	0.30	0.25	0.34	0.29	0.22	0.14	0.02	−0.11	−0.25	−0.40	−0.71	(−2.77)
FF	β^{MktRF}	$\overline{r}$	0.47	0.59	0.63	0.53	0.59	0.49	0.58	0.64	0.51	0.45	−0.02	(−0.06)
		β^{MktRF}_{Post}	0.55	0.67	0.73	0.80	0.90	0.95	1.05	1.16	1.30	1.47	0.91	(14.66)
		α	0.13	0.24	0.22	0.07	0.08	−0.03	0.02	0.01	−0.16	−0.28	−0.42	(−1.83)
	β^{SMB}	$\overline{r}$	0.48	0.48	0.69	0.67	0.61	0.55	0.71	0.61	0.54	0.37	−0.11	(−0.39)
		β^{SMB}_{Post}	−0.33	−0.06	0.11	0.16	0.34	0.39	0.48	0.63	0.71	0.96	1.30	(14.19)
		α	−0.00	−0.01	0.13	0.11	0.04	−0.04	0.10	−0.07	−0.13	−0.33	−0.32	(−1.78)
	β^{HML}	$\overline{r}$	0.23	0.39	0.46	0.61	0.75	0.45	0.62	0.70	0.62	0.72	0.50	(1.32)
		β^{HML}_{Post}	−0.78	−0.37	−0.06	0.03	0.15	0.24	0.34	0.43	0.60	0.92	1.70	(12.71)
		α	−0.18	0.02	0.04	0.16	0.26	−0.10	0.01	0.03	−0.17	−0.22	−0.04	(−0.13)
FFC	β^{MktRF}	$\overline{r}$	0.52	0.55	0.55	0.47	0.55	0.52	0.59	0.72	0.51	0.43	−0.09	(−0.25)
		β^{MktRF}_{Post}	0.67	0.72	0.76	0.86	0.90	0.95	1.04	1.15	1.21	1.39	0.72	(12.41)
		α	−0.07	−0.01	0.12	0.02	0.03	−0.03	0.07	0.20	−0.02	−0.02	0.04	(0.17)
	β^{SMB}	$\overline{r}$	0.48	0.49	0.70	0.69	0.58	0.58	0.67	0.51	0.61	0.32	−0.16	(−0.59)
		β^{SMB}_{Post}	−0.32	−0.05	0.04	0.15	0.40	0.38	0.54	0.59	0.74	0.94	1.26	(14.58)
		α	0.03	0.01	0.17	0.09	−0.03	0.03	0.11	−0.07	0.04	−0.20	−0.23	(−1.10)
	β^{HML}	$\overline{r}$	0.17	0.46	0.50	0.52	0.63	0.57	0.68	0.56	0.68	0.64	0.47	(1.31)
		β^{HML}_{Post}	−0.80	−0.36	−0.11	0.05	0.07	0.20	0.30	0.42	0.64	0.79	1.59	(12.05)
		α	−0.00	0.19	0.11	0.01	0.10	0.03	0.06	−0.12	−0.04	−0.21	−0.21	(−0.60)
	β^{MOM}	$\overline{r}$	0.40	0.50	0.52	0.53	0.63	0.65	0.63	0.38	0.45	0.67	0.26	(0.87)
		β^{MOM}_{Post}	−0.26	−0.09	−0.10	−0.05	−0.05	−0.03	0.03	0.08	0.06	0.06	0.32	(3.71)
		α	−0.18	−0.16	−0.02	0.02	0.16	0.22	0.16	−0.14	−0.07	0.11	0.29	(1.22)
FF5	β^{MktRF}	$\overline{r}$	0.61	0.54	0.53	0.50	0.56	0.54	0.55	0.49	0.69	0.44	−0.17	(−0.55)
		β^{MktRF}_{Post}	0.81	0.74	0.81	0.89	0.89	0.98	1.06	1.13	1.20	1.29	0.48	(5.75)
		α	0.22	0.06	0.02	−0.07	0.08	−0.01	−0.05	−0.11	0.12	−0.03	−0.25	(−0.95)
	β^{SMB5}	$\overline{r}$	0.47	0.44	0.73	0.67	0.60	0.60	0.69	0.59	0.57	0.35	−0.12	(−0.50)
		β^{SMB5}_{Post}	−0.29	−0.11	0.08	0.19	0.32	0.40	0.43	0.59	0.77	0.89	1.18	(13.71)
		α	0.06	−0.16	0.14	0.13	−0.03	0.02	0.07	−0.05	−0.05	−0.14	−0.20	(−1.19)
	β^{HML}	$\overline{r}$	0.31	0.35	0.68	0.51	0.50	0.43	0.69	0.59	0.66	0.79	0.48	(1.52)
		β^{HML}_{Post}	−0.42	−0.29	−0.25	−0.11	0.12	−0.02	0.14	0.40	0.67	0.90	1.32	(5.47)
		α	0.08	−0.07	0.26	−0.00	−0.11	−0.04	0.12	−0.13	−0.14	0.09	0.02	(0.06)
	β^{CMA}	$\overline{r}$	0.35	0.43	0.67	0.42	0.60	0.58	0.53	0.64	0.53	0.33	−0.02	(−0.07)
		β^{CMA}_{Post}	−0.77	−0.40	−0.19	−0.02	0.05	0.18	0.11	0.37	0.36	0.43	1.20	(5.02)
		α	0.06	0.02	0.30	−0.16	0.12	0.03	−0.02	0.05	−0.16	−0.43	−0.49	(−1.61)
	β^{RMW}	$\overline{r}$	0.34	0.44	0.56	0.55	0.53	0.65	0.57	0.63	0.58	0.61	0.27	(0.98)
		β^{RMW}_{Post}	−0.75	−0.43	−0.14	0.11	0.08	−0.01	0.08	0.18	0.08	0.16	0.91	(4.11)
		α	0.02	−0.02	0.06	−0.08	−0.02	0.13	0.02	0.06	0.05	0.13	0.10	(0.41)

Table 8: Security Market Plane and Betting Against Beta - International

This table presents estimates of the slopes of the security market plane and betting against beta effects with respect to betas on different factors using different factor models in international stock markets. Panel A presents results for Asia and Panel B presents results for Europe. The estimates of the security market plane slopes ($\lambda - \psi$) are calculated by regressing average portfolio excess returns on post-formation portfolio betas. The regression specification is $\overline{r_p} = \gamma + \sum_{j=1}^{n}(\lambda - \psi)^j \beta^j_{Post} + \epsilon_p$. The values of $\overline{r_p}$ and β^f_{Post} used in the regression are those of the decile portfolios reported in Table 7 for the given factor model. The estimates of the betting against beta effects (ψ) are calculated by taking the difference between the estimate of λ from Table 6 and the estimate of $\lambda - \psi$. The column labeled "Model" indicates the model used in the analysis. The column labeled "Factor" indicates the factor to which the values in the given row pertain. The column labeled "$\lambda - \psi$" presents the coefficient on β^j_{Post} from the regression. The column labeled "$t(\lambda - \psi)$" presents the t-statistic testing the null hypothesis that the slope coefficient, $\lambda - \psi$, is equal to zero. The column labeled "ψ" presents the estimates of ψ. The column labeled "$t(\psi)$" presents the t-statistic testing the null hypothesis that ψ is equal to zero, calculated by dividing ψ by the standard error of the estimate of $\lambda - \psi$.

Panel A: Asia

Model	Factor	$\lambda - \psi$	$t(\lambda - \psi)$	ψ	$t(\psi)$
CAPM	$MktRF$	0.03	(0.20)	0.56	(3.86)
FF	$MktRF$	0.08	(0.29)	0.51	(1.85)
	SMB	−0.56	(−3.97)	0.30	(2.10)
	HML	0.03	(0.18)	0.59	(3.92)
FFC	$MktRF$	0.06	(0.21)	0.53	(2.00)
	SMB	−0.58	(−4.73)	0.31	(2.57)
	HML	0.00	(0.01)	0.62	(4.65)
	MOM	−0.44	(−0.95)	1.20	(2.60)
FF5	$MktRF$	0.58	(2.19)	0.01	(0.05)
	$SMB5$	−0.41	(−3.13)	0.29	(2.19)
	HML	0.12	(0.70)	0.49	(2.78)
	CMA	0.21	(1.09)	0.17	(0.88)
	RMW	0.29	(2.70)	0.03	(0.27)

Panel B: Europe

Model	Factor	$\lambda - \psi$	$t(\lambda - \psi)$	ψ	$t(\psi)$
CAPM	$MktRF$	−0.26	(−3.05)	0.78	(9.21)
FF	$MktRF$	−0.08	(−0.80)	0.60	(6.02)
	SMB	0.02	(0.28)	0.03	(0.40)
	HML	0.29	(4.91)	0.03	(0.57)
FFC	$MktRF$	0.22	(1.12)	0.30	(1.53)
	SMB	0.01	(0.07)	0.04	(0.53)
	HML	0.15	(2.78)	0.17	(3.11)
	MOM	0.76	(2.83)	0.19	(0.69)
FF5	$MktRF$	0.07	(0.36)	0.45	(2.19)
	$SMB5$	−0.00	(−0.01)	0.11	(1.39)
	HML	0.17	(2.11)	0.15	(1.94)
	CMA	−0.05	(−0.54)	0.21	(2.42)
	RMW	0.18	(2.26)	0.18	(2.30)

Table 9: Arbitrage Portfolios - International

This table describes the performance of arbitrage portfolios for the non-market factors in the FF, FFC, and FF5 factor models in international stock markets. Panel A presents results for Asia and Panel B presents results for Europe. The objective of the arbitrage portfolio is to profit from the given factor's betting against beta effect while taking as little risk as possible. Details of the construction of the arbitrage portfolios are in Sections 4 and 5.5. The excess return of the arbitrage portfolio is taken to be the excess factor return minus the excess return of the hedge portfolio. The columns labeled "Model" and "Factor" indicate the factor model and factor, respectively, to which results in the given row pertain. The columns labeled "$\overline{r^{Arb}}$" and "$t(\overline{r^{Arb}})$" present the mean monthly excess return of the arbitrage portfolio and the t-statistic, adjusted following Newey and West (1987) using 3 lags, testing the null hypothesis that the mean arbitrage portfolio excess return is equal to zero. The columns labeled "ψ" and "λ" present the estimate of the betting against beta effect for the factor and the average factor excess return, respectively. The columns labeled σ^{Factor} and σ^{Arb} present the standard deviations of the monthly factor and arbitrage portfolio excess returns, respectively. The column labeled ρ shows the correlation between the factor excess returns and the hedge portfolio excess returns. The column labeled "$\overline{\sum w}$" presents the time-series average of the monthly sum of the weights of the decile portfolios in the hedge portfolio. The column labeled "$\overline{\sum |w|}$" presents the time-series average of the monthly sum of absolute values of the weights of the decile portfolios in the hedge portfolio.

Panel A: Asia

Model	Factor	$\overline{r^{Arb}}$	$t(\overline{r^{Arb}})$	ψ	λ	σ^{Factor}	σ^{Arb}	ρ	$\overline{\sum w}$	$\overline{\sum \|w\|}$
FF	SMB	−0.01	(−0.08)	0.30	−0.26	3.00	2.34	0.62	−0.24	1.24
	HML	0.46	(3.36)	0.59	0.62	3.12	2.17	0.72	−0.02	1.16
FFC	SMB	0.00	(0.01)	0.31	−0.26	3.00	2.28	0.65	−0.24	1.23
	HML	0.46	(3.39)	0.62	0.62	3.12	2.13	0.74	−0.01	1.18
	MOM	1.12	(5.63)	1.20	0.76	4.59	3.20	0.72	0.04	1.36
FF5	$SMB5$	0.07	(0.38)	0.29	−0.12	2.96	2.32	0.62	−0.23	1.32
	HML	0.37	(2.69)	0.49	0.62	3.12	2.23	0.71	−0.02	1.24
	CMA	0.41	(4.59)	0.17	0.38	2.36	1.57	0.75	−0.08	0.89
	RMW	0.25	(2.18)	0.03	0.32	2.81	1.76	0.78	−0.01	1.07

Panel B: Europe

Model	Factor	$\overline{r^{Arb}}$	$t(\overline{r^{Arb}})$	ψ	λ	σ^{Factor}	σ^{Arb}	ρ	$\overline{\sum w}$	$\overline{\sum \|w\|}$
FF	SMB	0.07	(0.66)	0.03	0.05	2.20	1.51	0.74	−0.21	1.85
	HML	0.20	(1.60)	0.03	0.32	2.53	1.56	0.80	−0.03	1.25
FFC	SMB	0.05	(0.55)	0.04	0.05	2.20	1.44	0.76	−0.21	1.84
	HML	0.21	(1.68)	0.17	0.32	2.53	1.58	0.79	−0.03	1.27
	MOM	0.96	(6.15)	0.19	0.94	4.13	2.59	0.79	−0.01	1.99
FF5	$SMB5$	0.04	(0.44)	0.11	0.11	2.15	1.38	0.77	−0.21	1.85
	HML	0.25	(1.94)	0.15	0.32	2.53	1.67	0.76	−0.04	1.34
	CMA	0.11	(1.17)	0.21	0.16	1.91	1.26	0.76	−0.02	1.05
	RMW	0.33	(4.51)	0.18	0.35	1.61	1.16	0.70	0.01	1.05

Table 10: Arbitrage Portfolio Correlations

This table presents time-series correlations between the excess returns of arbitrage portfolios. The columns labeled "Model" indicate the factor model to which results in the given portion of the table pertain. Panel A presents correlations between arbitrage portfolio excess returns for arbitrage portfolios formed with respect to different factors in the same factor model and same region. The top row of the table indicates the region to which the results in the given columns pertain. For each combination of model and region, the table presents the correlation matrix for the excess returns of the arbitrage portfolios for different factors. Panel B presents correlations for arbitrage portfolios constructed from the same factor in the same factor model in different regions. The column labeled "Factor" indicates the factor whose arbitrage portfolio excess returns are used to generate the results in the given row. The columns labeled "$\rho_{Region1,Region2}$" present the correlations between the excess returns of the arbitrage portfolios for the given factors in regions $Region1$ and $Region2$.

Panel A: Across Factors

		US			Asia			Europe		
Model	Factor									
FF		SMB			SMB			SMB		
	HML	−0.07			−0.01			−0.19		
FFC		SMB	HML		SMB	HML		SMB	HML	
	HML	−0.08			−0.05			−0.14		
	MOM	−0.03	−0.15		−0.01	−0.03		0.00	−0.14	
FF5		$SMB5$	HML	CMA	$SMB5$	HML	CMA	$SMB5$	HML	CMA
	HML	0.09			0.18			0.02		
	CMA	0.03	0.39		−0.05	0.35		−0.03	0.48	
	RMW	−0.05	−0.08	−0.30	−0.17	−0.29	−0.15	−0.14	−0.24	−0.18
Q		ME	IA							
	IA	0.03								
	ROE	0.01	−0.04							
SY		$SMBSY$	$PERF$							
	$PERF$	0.05								
	$MGMT$	0.02	−0.04							
DHS		$PEAD$								
	FIN	−0.03								
DMRS		SMB^*	HML^*	CMA^*						
	HML^*	0.13								
	CMA^*	0.15	0.55							
	RMW^*	−0.18	−0.48	−0.45						

Panel B: Across Regions

Model	Factor	$\rho_{\text{US,Asia}}$	$\rho_{\text{US,Europe}}$	$\rho_{\text{Asia,Europe}}$
FF	SMB	0.09	0.04	0.35
	HML	0.19	0.36	0.30
FFC	SMB	0.11	0.03	0.32
	HML	0.21	0.42	0.30
	MOM	0.32	0.52	0.33
FF5	$SMB5$	0.11	0.08	0.34
	HML	0.24	0.43	0.28
	CMA	0.06	0.15	0.15
	RMW	0.14	0.01	0.10

Table 11: Aritrage Portfolio TED Spread Regressions

This table presents the results of time-series regressions of arbitrage portfolio excess returns on the lagged TED spread and the contemporaneous change in the TED spread. The regression specification is $r_{k,t}^{Arb} = \gamma_0 + \gamma_1 TED_{t-1} + \gamma_2 \Delta TED_t + \nu_{k,t}$ where $r_{k,t}^{Arb}$ is the month t excess return of arbitrage portfolio k, TED_{t-1} is the TED spread as of the end of month $t-1$, and ΔTED_t is the TED spread as of the end of month t minus the TED spread as of the end of month $t-1$. The columns labeled "Model" and "Factor" indicate the factor model and factor, respectively, to which results in the given row pertain. The top row of the table indicates the region to which the results in the given columns pertain. For each combination of factor model, factor, and region, the columns labeled "TED_{t-1}" and "ΔTED_t" present the estimated slope coefficients γ_1 and γ_2, respectively, along with the associated t-statistics testing the null hypothesis that the slope coefficient is equal to zero (in parentheses).

		US		Asia		Europe	
Model	Factor	TED_{t-1}	$\Delta(TED_t)$	TED_{t-1}	$\Delta(TED_t)$	TED_{t-1}	$\Delta(TED_t)$
FF	SMB	0.13	0.01	−1.72	−1.05	−1.26	−1.12
		(0.72)	(0.03)	(−4.50)	(−1.54)	(−3.17)	(−3.04)
	HML	−0.06	−0.19	−0.04	0.38	−0.54	−0.52
		(−0.33)	(−0.52)	(−0.10)	(0.65)	(−1.90)	(−1.12)
FFC	SMB	0.04	−0.27	−1.77	−1.39	−1.03	−0.87
		(0.25)	(−0.77)	(−5.50)	(−2.19)	(−2.71)	(−2.68)
	HML	−0.10	−0.25	−0.04	0.30	−0.58	−0.33
		(−0.50)	(−0.56)	(−0.10)	(0.72)	(−1.97)	(−0.79)
	MOM	0.28	0.44	−1.40	0.01	−0.53	−1.08
		(0.77)	(0.72)	(−2.62)	(0.01)	(−1.15)	(−1.29)
FF5	$SMB5$	−0.10	0.09	−1.95	−1.25	−1.10	−0.70
		(−0.53)	(0.20)	(−5.21)	(−1.79)	(−3.18)	(−1.98)
	HML	−0.34	−0.29	−0.16	−0.04	−0.70	−0.06
		(−1.41)	(−0.94)	(−0.38)	(−0.06)	(−2.20)	(−0.14)
	CMA	0.02	−0.04	−0.22	0.54	−0.04	0.86
		(0.12)	(−0.11)	(−0.75)	(0.98)	(−0.12)	(3.12)
	RMW	0.09	0.40	−0.38	0.62	−0.10	0.16
		(0.70)	(1.27)	(−0.61)	(1.48)	(−0.53)	(0.48)
Q	ME	0.15	0.25				
		(0.64)	(0.32)				
	IA	−0.09	−0.20				
		(−0.47)	(−0.50)				
	ROE	0.34	0.84				
		(1.57)	(2.67)				
SY	$SMBSY$	0.18	−0.49				
		(1.02)	(−1.09)				
	$PERF$	0.62	1.14				
		(2.11)	(1.86)				
	$MGMT$	0.26	0.08				
		(1.75)	(0.26)				
DHS	$PEAD$	0.10	0.40				
		(0.50)	(1.15)				
	FIN	0.13	0.22				
		(0.43)	(0.39)				
DMRS	SMB^*	−0.21	−0.35				
		(−1.02)	(−1.13)				
	HML^*	−0.24	−0.29				
		(−1.18)	(−1.34)				
	CMA^*	0.03	−0.34				
		(0.25)	(−1.64)				
	RMW^*	0.13	0.23				
		(0.94)	(0.79)				

Table 12: Arbitrage Portfolio BAB Factor Regressions

This table presents the results of time-series regressions of arbitrage portfolio excess returns on the betting against beta factors of FP. The regression specification is $r_{k,t}^{Arb} = \alpha_k + \beta_k^{FMAX} BAB_t + \nu_{k,t}$ where $r_{k,t}^{Arb}$ is the month t excess return of arbitrage portfolio k and BAB_t is the month t betting against beta factor excess return. Regressions in each region use the betting against beta factor for the given region as the independent variable in the regression. The columns labeled "Model" and "Factor" indicate the factor model and factor, respectively, to which results in the given row pertain. The top row of the table indicates the region to which the results in the given columns pertain. For each combination of factor model, factor, and region, the table presents the estimated intercept (column labeled "α") and slope coefficient (column labeled "β^{BAB}"), along with the associated t-statistics testing the null hypothesis that the coefficient is equal to zero (in parentheses).

		US		Asia		Europe	
Model	Factor	α	β^{BAB}	α	β^{BAB}	α	β^{BAB}
FF	SMB	0.17	0.04	−0.17	0.19	−0.05	0.13
		(2.40)	(1.43)	(−1.00)	(3.65)	(−0.42)	(2.97)
	HML	0.17	0.12	0.41	0.06	0.15	0.04
		(2.39)	(4.20)	(2.64)	(1.19)	(1.29)	(1.44)
FFC	SMB	0.14	0.04	−0.12	0.14	−0.07	0.13
		(2.07)	(1.29)	(−0.69)	(2.83)	(−0.70)	(3.19)
	HML	0.17	0.11	0.43	0.03	0.17	0.04
		(2.27)	(3.69)	(2.76)	(0.64)	(1.42)	(1.18)
	MOM	0.45	0.17	1.04	0.09	0.75	0.22
		(2.83)	(1.61)	(4.29)	(1.05)	(4.47)	(3.80)
FF5	$SMB5$	0.16	0.05	−0.08	0.18	−0.07	0.12
		(2.44)	(1.78)	(−0.46)	(3.31)	(−0.73)	(3.33)
	HML	0.17	0.15	0.32	0.06	0.18	0.08
		(2.12)	(5.51)	(2.11)	(1.12)	(1.39)	(2.19)
	CMA	0.31	0.02	0.40	0.01	0.08	0.03
		(4.49)	(0.74)	(4.03)	(0.26)	(0.82)	(0.75)
	RMW	0.22	0.03	0.28	−0.03	0.30	0.04
		(2.98)	(0.77)	(2.30)	(−0.78)	(3.82)	(1.22)
Q	ME	0.18	0.03				
		(2.27)	(1.06)				
	IA	0.34	0.02				
		(5.64)	(0.62)				
	ROE	0.47	0.07				
		(5.30)	(1.55)				
SY	$SMBSY$	0.30	0.07				
		(4.22)	(2.27)				
	$PERF$	0.54	0.09				
		(4.34)	(1.06)				
	$MGMT$	0.49	0.07				
		(6.46)	(2.42)				
DHS	$PEAD$	0.53	0.04				
		(5.32)	(1.06)				
	FIN	0.53	0.13				
		(4.83)	(2.62)				
DMRS	SMB^*	0.19	0.05				
		(2.60)	(1.28)				
	HML^*	0.24	0.05				
		(3.16)	(2.14)				
	CMA^*	0.25	−0.02				
		(4.15)	(−1.11)				
	RMW^*	0.21	−0.02				
		(3.12)	(−0.51)				

Table 13: Arbitrage Portfolio $FMAX$ Factor Regressions

This table presents the results of time-series regressions of arbitrage portfolio excess returns on the lottery demand factor of Bali et al. (2017). The regression specification is $r_{k,t}^{Arb} = \alpha_k + \beta_k^{FMAX} FMAX_t + \nu_{k,t}$ where $r_{k,t}^{Arb}$ is the month t excess return of arbitrage portfolio k and $FMAX_t$ is the negative of the month t lottery demand factor excess return. The columns labeled "Model" and "Factor" indicate the factor model and factor, respectively, to which results in the given row pertain. The top row of the table indicates the region to which the results in the given columns pertain. For each combination of factor model, factor, and region, the table presents the estimated intercept (column labeled "α") and slope coefficient (column labeled "β^{FMAX}"), along with the associated t-statistics testing the null hypothesis that the coefficient is equal to zero (in parentheses).

		US		Asia		Europe	
Model	Factor	α	β^{FMAX}	α	β^{FMAX}	α	β^{FMAX}
FF	SMB	0.23	−0.06	0.04	−0.08	0.11	−0.07
		(3.76)	(−3.52)	(0.23)	(−3.11)	(1.14)	(−3.29)
	HML	0.20	0.11	0.42	0.06	0.15	0.08
		(3.27)	(5.07)	(3.19)	(2.04)	(1.29)	(2.69)
FFC	SMB	0.21	−0.07	0.05	−0.08	0.08	−0.04
		(3.53)	(−3.71)	(0.32)	(−2.98)	(0.85)	(−2.17)
	HML	0.20	0.11	0.42	0.07	0.16	0.08
		(3.02)	(4.90)	(3.24)	(2.78)	(1.35)	(2.36)
	MOM	0.56	0.05	1.09	0.04	0.94	0.04
		(4.27)	(0.66)	(5.38)	(0.91)	(5.69)	(0.66)
FF5	$SMB5$	0.23	−0.03	0.10	−0.06	0.07	−0.04
		(3.79)	(−2.04)	(0.60)	(−2.05)	(0.74)	(−2.13)
	HML	0.24	0.10	0.34	0.06	0.21	0.08
		(3.06)	(4.42)	(2.52)	(2.06)	(1.70)	(2.62)
	CMA	0.32	0.02	0.37	0.06	0.07	0.06
		(4.92)	(0.95)	(4.31)	(2.98)	(0.83)	(2.84)
	RMW	0.19	0.09	0.24	0.02	0.32	0.02
		(2.88)	(2.42)	(2.08)	(0.69)	(4.24)	(1.08)
Q	ME	0.23	−0.04				
		(3.23)	(−1.66)				
	IA	0.35	0.01				
		(6.34)	(0.76)				
	ROE	0.48	0.08				
		(5.99)	(2.81)				
SY	$SMBSY$	0.37	−0.01				
		(5.65)	(−0.51)				
	$PERF$	0.57	0.07				
		(5.35)	(1.32)				
	$MGMT$	0.50	0.09				
		(7.46)	(5.46)				
DHS	$PEAD$	0.56	0.02				
		(6.30)	(0.40)				
	FIN	0.60	0.11				
		(6.17)	(2.98)				
DMRS	SMB^{*}	0.27	−0.06				
		(4.10)	(−2.22)				
	HML^{*}	0.26	0.03				
		(3.60)	(2.01)				
	CMA^{*}	0.24	−0.01				
		(4.23)	(−1.05)				
	RMW^{*}	0.17	0.05				
		(2.81)	(1.66)				

Table 14: Betting Against Beta and Capital Gains Overhang

This table presents estimates of the differences in security market plane slopes with respect to betas on different factors for stocks with different levels of capital gains overhang (CGO). At the end of each month t, all stocks in the sample are sorted into quintiles based on an ascending sort of capital gains overhang (CGO), calculated following Grinblatt and Han (2005). Within each quintile of CGO, all stocks are then sorted into decile portfolios based on an ascending sort of one of the measures of beta using exactly the same procedure as was used to generate the results in Table 2 (for US stocks) or Table 7 (for international stocks). The value-weighted average month $t+1$ excess return for each portfolio is then calculated. Using only the beta-sorted decile portfolios constructed from stocks in the top and bottom CGO quintiles, I regress the mean excess returns of the portfolios on the post-formation betas and the post-formation betas interacted with a high-CGO indicator. The regression specification is $\overline{r_p} = \Psi + \sum_{j \in \{M\}} \gamma_{1,j} \beta^j_{Post,p} + \sum_{j \in \{M\}} \gamma_{2,j} \beta^j_{Post,p} \times I_{HighCGO} + \epsilon_p$, where $\overline{r_p}$ is the mean excess return of portfolio p, $\beta^j_{Post,p}$ is portfolio p's post-formation exposure to factor j, and $I_{HighCGO}$ is an indicator set to 1 for portfolios of stocks in the top CGO quintile. The columns labeled "Model" and "Factor" indicate the factor model and factor, respectively, to which results in the given row pertain. The top row of the table indicates the region to which the results in the given columns pertain. The columns labeled "γ_2" and "$t(\gamma_2)$" present the estimates of $\gamma_{2,j}$ and associated t-statistics testing the null hypothesis that the value of γ_2 is equal to zero.

		US		Asia		Europe	
Model	Factor	γ_2	$t(\gamma_2)$	γ_2	$t(\gamma_2)$	γ_2	$t(\gamma_2)$
CAPM	$MktRF$	0.45	6.33	0.61	4.80	0.29	3.53
FF	$MktRF$	0.06	0.47	0.04	0.26	0.36	3.95
	SMB	0.99	6.45	0.72	2.72	0.31	1.63
	HML	−0.06	−0.33	−1.05	−3.63	0.12	0.57
FFC	$MktRF$	1.16	3.55	0.44	1.54	0.05	0.23
	SMB	0.73	4.15	0.36	1.30	0.69	3.00
	HML	−0.32	−1.95	−0.85	−2.54	−0.16	−0.78
	MOM	0.78	1.17	0.16	0.22	0.63	0.99
FF5	$MktRF$	−0.45	−2.08	0.17	0.86	0.24	1.85
	$SMB5$	1.05	5.15	0.11	0.39	0.28	1.26
	HML	0.37	1.10	−0.72	−1.84	−0.33	−1.25
	CMA	0.32	1.02	−0.25	−0.67	−0.23	−0.86
	RMW	−0.58	−2.18	−0.19	−0.76	0.12	0.48
Q	$MKTQ$	−0.20	−0.83				
	ME	0.59	2.98				
	IA	−0.12	−0.69				
	ROE	−0.71	−2.33				
SY	$MktRF$	−0.06	−0.24				
	$SMBSY$	0.82	4.49				
	$PERF$	−0.47	−0.82				
	$MGMT$	−0.71	−3.53				
DHS	$MktRF$	0.68	2.70				
	$PEAD$	0.15	0.46				
	FIN	−0.55	−2.30				
DMRS	$MktRF^*$	−0.25	−1.34				
	SMB^*	0.35	2.11				
	HML^*	0.10	0.37				
	CMA^*	0.20	1.12				
	RMW^*	−0.70	−2.78				